Inter-Industry Wage Differentials: International Evidence from Micro Data

Luisa Zanchi

Thesis submitted for assessment with a view to obtaining the Degree of Doctor of the European University Institute

Florence, June 1997
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Luisa Zanchi

The Thesis Committee consists of:

Prof. Giorgio Brunello, University of Udine
" Alan Manning, London School of Economics
" John Micklewright, EUI and UNICEF, Florence, Supervisor
" Robert Waldmann, EUI
Acknowledgements

I am grateful to my supervisor, John Micklewright, for his many ideas and suggestions. His encouragement has been vital in preventing me from taking research directions leading nowhere and from feeling completely hopeless as an economist. I am also indebted to Robert Waldmann, for his unfailing support over the years, and the other members of the thesis committee, Giorgio Brunello and Alan Manning.

I gratefully acknowledge the help of many people who have, in a variety of ways, advised and assisted me at some stage, in particular Karim Abadir, Paula Adam, Tindara Addabbo, Marta Aloi, Marco Becht, Jacqueline Bourgonje, Fabio Canova, Herman Cesar, Gianni De Fraja, Christian Dustmann, Tilman Ehrbeck, Stefania Fabrizio, Gabriele Fiorentini, Mariolina Garofalo, Marcia Gastaldo, João Gata, Bill Gerrard, Gianna Giannelli, Maurice Glasman, Les Godfrey, Francis Green, David Harvie, Dorothea Herreiner, Andrew Hildreth, John Hutton, Regina Kaiser, Humberto Lopez, Jochen Lorentzen, Agustin Maravall, Annamaria Menichini, Peter Møllgaard, Chris Orme, Alessandra Pelloni, Louis Phlips, Kevin Reilly, Götz Rohwer, Harald Sonnberger, Jessica Spataro, Elena Stancanelli, Giovanni Urga, Paola Valbonesi and Mel Weeks.

The German Socio-Economic Panel (SOEP) data set was made available under the responsibility of Hans Peter Blossfeld, whose cooperation is also gratefully acknowledged.

Finally, I would like to thank all the participants in workshops at the Universities of York and Leeds, where I have been working in the last three years, and the VI Convegno Nazionale di Economia del Lavoro (Bergamo, 1991), the VII Annual Congress of the EEA (Dublin, 1992), the VIII Convegno Nazionale di Economia del Lavoro (Salerno, 1993), and the Royal Economic Society Conference 1995 (Canterbury), where I have presented parts of the thesis. Their generous comments have contributed to improve it greatly.
Contents

1 Introduction ....................................................................................................................... 1
   References .................................................................................................................. 11

2 Theoretical Framework and the Measurement of Inter-Industry Wage Differentials ................................................................. 13
   2.1 Introduction ........................................................................................................... 13
   2.2 Competitive Theories: Human Capital Theory and the Theory of Compensating Differentials .................................................. 19
   2.3 Non-Competitive Theories: Efficiency Wage Models and Insider- Outsider Theory .................................................................... 27
   2.4 Empirical Implications for the Inter-Industry Wage Structure ................................ 31
   2.5 The Degree of Centralization of Wage Bargaining .............................................. 42
   2.6 Institutional Conditions for Wage Bargaining in the Countries Considered .... 44
      2.6.1 The United States ......................................................................................... 45
      2.6.2 Canada ......................................................................................................... 45
      2.6.3 Australia ..................................................................................................... 46
      2.6.4 Germany ..................................................................................................... 47
      2.6.5 The Netherlands ......................................................................................... 48
      2.6.6 Austria ....................................................................................................... 49
      2.6.7 Sweden ..................................................................................................... 50
   2.7 Conclusions ............................................................................................................ 51
      References ............................................................................................................ 53

3 Analyses of the Inter-Industry Wage Structure with Aggregate Industry Wage Data .................................................................................... 61
   3.1 Introduction ........................................................................................................... 61
3.2 Testing for the Statistical Significance of Product-Moment Correlations. Rank
Correlations and Coefficients of Concordance .................................................... 64
3.2.1 The Pearson Product-Moment Correlation ............................................. 66
3.2.2 The Spearman Rank Correlation ............................................................... 75
3.2.3 The Coefficient of Concordance ............................................................... 76
3.3 Stability of Wage Structures over Time ....................................................... 83
3.4 Stability of Wage Structures across Countries ............................................. 102
3.5 Aggregate Industry Wage Data versus Micro Data Analyses ......................... 118
3.6 Conclusions .............................................................................................................. 131
References ................................................................................................................... 132

4 Inter-Industry Wage Differentials in Germany: Empirical Evidence from the
"Socio-Economic Panel" and a Comparison with the U.S., Australia, Austria and
Sweden .............................................................................................................. .............. 135
4.1 Introduction .............................................................................................................. 135
4.2 Data, Sub-Sample Characteristics, Model Specification and Construction of the
Variables .................................................................................................................... 137
4.3 Basic Results ............................................................................................................ 149
4.4 Comparisons with Evidence for the U.S., Australia, Austria and Sweden,
Based on Micro Data ............................................................................................. 159
4.5 Conclusions ............................................................................................................... 173
Appendix 4.A: SOEP, Wave 1 (1984) Variables Involved in the Selection of
the Sub-Sample and in the Construction of the Model Variables ...................... 174
Appendix 4.B: Estimated Wage Equations in the Sample Selection Model ........ 186
Appendix 4.C: Estimated Wage Differentials for Inter-Country Comparisons 195
References ................................................................................................................. 215

5 Cross-Country Comparisons of the Inter-Industry Wage Structure: Empirical
Evidence for the U.S., Canada, Australia, Germany and the Netherlands with the
"Luxembourg Income Study" Data-Bank ................................................................. 217
5.1 Introduction .............................................................................................................. 217
5.2 Empirical Evidence: Data, Sub-Samples, and Variables ................. 219
  5.2.1 The "Luxembourg Income Study" (LIS) Data-Bank ............. 219
  5.2.2 The Country Data-Sets Used ................................. 223
  5.2.3 Sub-Samples Characteristics .................................. 226
  5.2.4 Estimated Wage Equations: Model Specification and Variables
                       Definition ......................................................... 231
5.3 Empirical Evidence: Main Results ........................................ 241
5.4 Cross-Country Comparisons of Inter-Industry Wage Structures: Correlation
                   Coefficients and Minimum Distance Chi-Square Tests ...... 253
  5.4.1 Pearson and Spearman Correlation Coefficients ............... 253
  5.4.2 Minimum Distance Chi-Square Tests .............................. 258
5.5 Conclusions ............................................................................. 262

Appendix 5.A: LIS Variables Involved in the Selection of the Sub-Samples and
             in the Construction of the Regression Variables ............ 265
Appendix 5.B: Effects of Selection Criteria on the Sub-Samples Size ...... 287
Appendix 5.C: Estimated Wage Equations ...................................... 291
Appendix 5.D: Comparisons between Evidence from LIS Data and Evidence
               from Other Sources: The United States, Australia, and Germany 306
Appendix 5.E: Minimum Distance Estimation ................................ 315
Appendix 5.F: MATLAB Program for the Minimum Distance Chi-Square
               Test ................................................................. 318
References ...................................................................................... 321

6 Summary and Conclusions .......................................................... 322

Appendix Alternative Parameterizations of Dummy Variable Models ...... 326
  A.1 Introduction ........................................................................ 326
  A.2 Alternative Parameterizations of a Model with Dummy Variables . 328
  A.3 Relationships between the Alternative Parameterizations ...... 334
     A.3.1 Relationship between Model (A.1) and Model (A.2) ....... 335
     A.3.2 Relationship between Model (A.1) and Model (A.3) ....... 339
     A.3.3 Relationship between Model (A.2) and Model (A.3) ....... 343
<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.1</td>
<td>Krueger and Summers's industry wage structure over time in the U.S.: estimated Pearson correlation coefficients, respective standard errors and two-sided 99% confidence intervals, for log average annual earnings of full-time equivalent employees, in nine major industries.</td>
</tr>
<tr>
<td>3.2</td>
<td>Krueger and Summers's industry wage structure over time in the U.S.: estimated Pearson correlation coefficients and confidence intervals based on t and z transformations, for log average annual earnings of full-time equivalent employees, in nine major industries.</td>
</tr>
<tr>
<td>3.3</td>
<td>Gittleman and Wolff's industry wage differentials over time within countries: estimated Pearson correlation coefficients with 1985, respective standard errors and two-sided 99% confidence intervals, for all industries.</td>
</tr>
<tr>
<td>3.4</td>
<td>Gittleman and Wolff's industry wage differentials over time within countries: estimated Pearson correlation coefficients with 1985 and confidence intervals based on t and z transformations, for all industries.</td>
</tr>
<tr>
<td>3.5</td>
<td>Gittleman and Wolff's industry wage differentials over time within countries: estimated Spearman correlation coefficients with 1985 and tests of their statistical significance, for all industries.</td>
</tr>
<tr>
<td>3.6</td>
<td>Gittleman and Wolff's industry wage differentials over time within countries: estimated coefficients of concordance over the period 1970-85 and tests of their statistical significance, for all industries.</td>
</tr>
<tr>
<td>3.7</td>
<td>Krueger and Summers's industry wage structures across countries: estimated Pearson correlation coefficients and confidence intervals based on t and z transformations, for log average manufacturing wages, 1982.</td>
</tr>
<tr>
<td>3.8</td>
<td>Gittleman and Wolff's industry wage structure across countries: estimated Pearson correlation coefficients with U.S. industry wage differentials and confidence intervals based on t and z transformations, for all industries.</td>
</tr>
</tbody>
</table>
3.9 Gittleman and Wolff's industry wage structure across countries: estimated Pearson correlation coefficients with U.S. industry wage differentials and confidence intervals based on $t$ and $z$ transformations, for manufacturing industries .......................................................... 111

3.10 Gittleman and Wolff's industry wage structure across countries: estimated coefficients of concordance for selected countries and sectors and tests of their statistical significance, for all industries and manufacturing industries ......................................................... 114

3.11 Comparison between Krueger and Summers's and Gittleman and Wolff's industry wage structures across countries: estimated Pearson correlation coefficients with the U.S. industry wage structure, for manufacturing industries .......................................................... 117

3.12 Simulated data for individual wages and estimated inter-industry wage differentials .......................................................... 119

4.1 Estimated wage differentials in a sample selection model for two-digit industries, 1984: deviations from the employment-weighted mean differential (unadjusted OLS standard errors in parentheses) ...................... 150

4.2 Estimated wage differentials without controls for human capital and working conditions for the U.S., Germany and Sweden: deviations from the employment-weighted mean differential ...................... 164

4.3 Estimated wage differentials with controls for human capital and working conditions for the U.S., Australia, Germany, Austria and Sweden: deviations from the employment-weighted mean differential .......................................................... 165

4.4 Correlations of inter-industry wage differentials in deviation form estimated without and with controls for human capital and working conditions (one-sided p-values in parentheses) ...................... 171

4.B1 Estimated PROBIT overtime work equation in a sample selection model with controls for human capital and working conditions, 1984 (standard errors in parentheses) .......................................................... 187
4.B2 Estimated wage equation in a sample selection model without controls for human capital and working conditions, 1984 (standard errors in parentheses) ........................................... 190

4.B3 Estimated wage equation in a sample selection model with controls for human capital and working conditions, 1984 (standard errors in parentheses) ........................................... 191

4.C1 Wage differentials for the UNITED STATES and AUSTRALIA: deviations from the employment-weighted mean differential. Aggregation of the original differentials into a common classification of industry sectors by employment-weighted averages ........... 195

4.C2 Wage differentials for the UNITED STATES and GERMANY: deviations from the employment-weighted mean differential. Aggregation of the original differentials into a common classification of industry sectors by employment-weighted averages ........... 196

4.C3 Wage differentials for the UNITED STATES and AUSTRIA: deviations from the employment-weighted mean differential. Aggregation of the original differentials into a common classification of industry sectors by employment-weighted averages ........... 197

4.C4 Wage differentials for the UNITED STATES and SWEDEN: deviations from the employment-weighted mean differential. Aggregation of the original differentials into a common classification of industry sectors by employment-weighted averages ........... 198

4.C5 Wage differentials for AUSTRALIA and GERMANY: deviations from the employment-weighted mean differential. Aggregation of the original differentials into a common classification of industry sectors by employment-weighted averages ........... 199

4.C6 Wage differentials for AUSTRALIA and AUSTRIA: deviations from the employment-weighted mean differential. Aggregation of the original differentials into a common classification of industry sectors by employment-weighted averages ........... 200
4.C7 Wage differentials for AUSTRALIA and SWEDEN: deviations from the employment-weighted mean differential. Aggregation of the original differentials into a common classification of industry sectors by employment-weighted averages ............................................................... 201

4.C8 Wage differentials for GERMANY and AUSTRIA: deviations from the employment-weighted mean differential. Aggregation of the original differentials into a common classification of industry sectors by employment-weighted averages ............................................................... 202

4.C9 Wage differentials for GERMANY and SWEDEN: deviations from the employment-weighted mean differential. Aggregation of the original differentials into a common classification of industry sectors by employment-weighted averages ............................................................... 203

4.C10 Wage differentials for AUSTRIA and SWEDEN: deviations from the employment-weighted mean differential. Aggregation of the original differentials into a common classification of industry sectors by employment-weighted averages ............................................................... 204

5.1 Distribution of male employment by sector in the LIS samples and in the populations: employment per sector and percentage of total employment per sector ..................................................................................... 238

5.2 Estimated wage differentials without controls for human capital: deviations from the employment-weighted mean differential (standard errors of the differentials in deviation form in parentheses) .......... 242

5.3 Estimated wage differentials with controls for human capital: deviations from the employment-weighted mean differential (standard errors of the differentials in deviation form in parentheses) .......... 244

5.4 Correlations of inter-industry wage differentials in deviation form estimated without and with controls for human capital (one-sided p-values in parentheses) ................................................................. 254

5.5 Minimum distance $\chi^2$ tests of equality restrictions on inter-industry wage structures: wage differentials in deviation form ................................................................. 261
5.C1 UNITED STATES 1986: Estimated wage equation without controls for human capital (OLS standard errors in parentheses). Dependent variable: logarithm of individual hourly wage ............................................. 291
5.C2 CANADA 1987: Estimated wage equation without controls for human capital (OLS standard errors in parentheses). Dependent variable: logarithm of individual hourly wage ............................................................ 292
5.C3 AUSTRALIA 1986: Estimated wage equation without controls for human capital (OLS standard errors in parentheses). Dependent variable: logarithm of individual hourly wage ............................................. 293
5.C4 GERMANY 1985: Estimated wage equation without controls for human capital (OLS standard errors in parentheses). Dependent variable: logarithm of individual hourly wage ............................................. 294
5.C5 NETHERLANDS 1987: Estimated wage equation without controls for human capital (OLS standard errors in parentheses). Dependent variable: logarithm of individual hourly wage ............................................. 295
5.C6 UNITED STATES 1986: Estimated wage equation with controls for human capital (OLS standard errors in parentheses). Dependent variable: logarithm of individual hourly wage ............................................. 296
5.C7 CANADA 1987: Estimated wage equation with controls for human capital (OLS standard errors in parentheses). Dependent variable: logarithm of individual hourly wage ............................................. 298
5.C8 AUSTRALIA 1986: Estimated wage equation with controls for human capital (OLS standard errors in parentheses). Dependent variable: logarithm of individual hourly wage ............................................. 300
5.C9 GERMANY 1985: Estimated wage equation with controls for human capital (OLS standard errors in parentheses). Dependent variable: logarithm of individual hourly wage ............................................. 302
5.C10 NETHERLANDS 1987: Estimated wage equation with controls for human capital (OLS standard errors in parentheses). Dependent variable: logarithm of individual hourly wage ............................................. 304
5.D1 UNITED STATES: Estimated wage differentials with controls for human capital: deviations from the employment-weighted mean differential (standard errors in parentheses) ............................................... 308
5.D2 AUSTRALIA: Estimated wage differentials with controls for human capital: deviations from the employment-weighted mean differential (standard errors in parentheses) ............................................... 310
5.D3 GERMANY: Estimated wage differentials with controls for human capital: deviations from the employment-weighted mean differential (standard errors in parentheses) ............................................... 313
List of Figures

3.1 Frequency curves for the correlation coefficient $r$ of samples with $n = 10, 50$ ................................................. 69
3.2 Krueger and Summers's industry wage structure over time in the U.S.: Pearson correlation coefficients with 1984 and two-sided 99% confidence intervals ................................................. 84
3.3 Gittleman and Wolff's industry wage differentials over time within countries: Pearson correlation coefficients between 1985 and 1980 and two-sided 99% confidence intervals ................................................. 93
3.4 Gittleman and Wolff's industry wage differentials over time within countries: Pearson correlation coefficients between 1985 and 1975 and two-sided 99% confidence intervals ................................................. 94
3.5 Gittleman and Wolff's industry wage differentials over time within countries: Pearson correlation coefficients between 1985 and 1970 and two-sided 99% confidence intervals ................................................. 94
3.6 Krueger and Summers's and Gittleman and Wolff's industry wage structures across countries: Pearson correlation coefficients with the U.S. industry wage structure ................................................. 117
4.1 Estimated industry wage differentials with and without controls: Germany, 1984 ................................................. 156
4.2 Industry wage differentials estimated without controls ................................................. 166
4.3 Industry wage differentials estimated with controls ................................................. 166
4.C1 Industry wage differentials estimated with controls: UNITED STATES and AUSTRALIA ................................................. 205
4.C2.1 Industry wage differentials estimated without controls: UNITED STATES and GERMANY ................................................. 206
4.C2.2 Industry wage differentials estimated with controls: UNITED STATES and GERMANY ................................................. 206
4.C3 Industry wage differentials estimated with controls: UNITED STATES and AUSTRIA ................................................. 207
<table>
<thead>
<tr>
<th>Section</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.C4.1</td>
<td>Industry wage differentials estimated without controls: UNITED STATES and SWEDEN</td>
<td>208</td>
</tr>
<tr>
<td>4.C4.2</td>
<td>Industry wage differentials estimated with controls: UNITED STATES and SWEDEN</td>
<td>208</td>
</tr>
<tr>
<td>4.C5</td>
<td>Industry wage differentials estimated with controls: AUSTRALIA and GERMANY</td>
<td>209</td>
</tr>
<tr>
<td>4.C6</td>
<td>Industry wage differentials estimated with controls: AUSTRALIA and AUSTRIA</td>
<td>210</td>
</tr>
<tr>
<td>4.C7</td>
<td>Industry wage differentials estimated with controls: AUSTRALIA and SWEDEN</td>
<td>211</td>
</tr>
<tr>
<td>4.C8</td>
<td>Industry wage differentials estimated with controls: GERMANY and AUSTRIA</td>
<td>212</td>
</tr>
<tr>
<td>4.C9.1</td>
<td>Industry wage differentials estimated without controls: GERMANY and SWEDEN</td>
<td>213</td>
</tr>
<tr>
<td>4.C9.2</td>
<td>Industry wage differentials estimated with controls: GERMANY and SWEDEN</td>
<td>213</td>
</tr>
<tr>
<td>4.C10</td>
<td>Industry wage differentials estimated with controls: AUSTRIA and SWEDEN</td>
<td>214</td>
</tr>
<tr>
<td>5.1</td>
<td>Employment distribution by sector: samples (LIS), male workers</td>
<td>239</td>
</tr>
<tr>
<td>5.2</td>
<td>Employment distribution by sector: populations (OECD), male workers</td>
<td>239</td>
</tr>
<tr>
<td>5.3</td>
<td>Estimated wage differentials without controls for human capital</td>
<td>251</td>
</tr>
<tr>
<td>5.4</td>
<td>Estimated wage differentials with controls for human capital</td>
<td>251</td>
</tr>
<tr>
<td>5.D1</td>
<td>UNITED STATES: Estimated wage differentials with controls for human capital</td>
<td>308</td>
</tr>
<tr>
<td>5.D2</td>
<td>AUSTRALIA: Estimated wage differentials with controls for human capital</td>
<td>310</td>
</tr>
<tr>
<td>5.D3</td>
<td>GERMANY: Estimated wage differentials with controls for human capital</td>
<td>313</td>
</tr>
<tr>
<td>A.1</td>
<td>Model (A.1)</td>
<td>330</td>
</tr>
<tr>
<td>A.2</td>
<td>Model (A.2)</td>
<td>333</td>
</tr>
<tr>
<td>A.3</td>
<td>Model (A.3)</td>
<td>334</td>
</tr>
</tbody>
</table>
Chapter 1

Introduction

"A few years ago we hired a new secretary in my department. She was smart and efficient and we were pleased to have her. Much to our dismay, after just a few months she was offered and accepted a job from an IBM facility in a nearby city. She told me that she had been on a waiting list there for a year or so, and would be a fool to turn IBM down since they paid so much more than any of the other local employers. I wondered at the time whether her marginal product typing IBM interoffice memos could be that much higher than it would be typing manuscripts and referee reports, and/or why IBM should find it profitable to pay much more than the going wage. (...) These observations seem to violate the law of one price, a fundamental component of the theory of competitive markets." (Thaler, 1989, pp.181-182).

Several empirical studies of the inter-industry wage structure tend to show results which do not seem consistent with the competitive model of the labour market. Pieces of casual evidence like the one just quoted are confirmed by a number of more detailed investigations. These suggest that some industries might pay higher wages than others, even when differences in (observable) labour quality are taken into proper account. In other words, equal employees may not be paid equal wages across industries. Inter-industry wage differentials also seem a very stable phenomenon over time, across countries and across occupations. According to existing work, today’s high- and low-wage industries tend to be the same as those at the beginning of this century (Slichter, 1950; Krueger and Summers, 1987) and, moreover, have remained in these relative positions during the whole intervening period (Krueger and Summers, 1987); high- and low-wage industries appear to be the same in several countries, especially developed capitalist economies (Krueger and Summers, 1987; Gittleman and Wolff, 1993); and, wage differentials seem to be stable with respect to different occupations within the same industry (Katz and Summers, 1989).

Some of these striking results are based on simple average industry wages derived from aggregate data sources, of the type usually published by international organizations like...
the OECD and the ILO. A more recent approach to the proof of the existence and the measurement of the importance of inter-industry wage differentials relies instead on large micro data-sets containing individual level information about workers' income and personal characteristics. It consists in the estimation of earnings functions of human capital theory (Becker, 1967; Mincer, 1974), enriched with a set of industry dummy variables which try to capture the specific effect of industry affiliation. The first examples of this kind of analysis were provided for the United States, using data from the Current Population Survey (CPS) (Dickens and Katz, 1987a and 1987b; Krueger and Summers, 1987 and 1988; Katz and Summers, 1989). All these studies invariably found large and highly significant inter-industry wage differentials, even after controlling for individual characteristics.

Before one can regard this measure of inter-industry wage differentials as genuine evidence against the theory of competitive markets, two obvious explanations must be ruled out: compensating wage differentials and unobservable labour quality. The theory of compensating differences implies that high wages might simply compensate workers for some undesirable aspect of their working conditions in particular industries (the mining industry is a typical example). The strategy usually adopted to test this hypothesis consists in adding a set of (measurable) job characteristic variables to the estimated wage equation (Brown, 1980).

The unobservable labour quality problem is much harder to tackle. A first possible approach is to evaluate the impact of observable labour quality on industry wage effects. Unobservable labour quality is likely to be correlated with observable quality and if inter-industry wage differentials are due to differences in unobservable labour quality, then the inclusion of observable labour quality variables in the wage equation should substantially reduce the industry differentials (Krueger and Summers, 1988). Some researchers however regard this argument as inadequate, since wage equations estimated with individual data explain in general only a small proportion of the overall variability of wages (Murphy and Topel, 1987). A second approach is to consider evidence from longitudinal data and estimate wage equations with techniques that control for fixed effects. Innate ability and other aspects of unobservable labour quality are in fact supposed to remain constant over time. This method implies that one is actually looking at workers who change jobs and switch between industries during the observed period and, therefore, may entail complex problems of measurement error and selectivity bias. Evidence from longitudinal data is far from uncontroversial (for example, Krueger and Summers, 1988 versus Murphy and Topel, 1987 and Kean, 1993). These
conflicting results are rather difficult to evaluate, since the various studies tend to use different data sources and different procedures (Thaler, 1989).

Other possible explanations of the inter-industry wage differentials observed in wage equations estimated with individual data belong to the class of non-competitive theories of the labour market. A rationale for the existence of significant industry effects is provided both by efficiency wage models (Krueger and Summers, 1988) and by the insider-outsider theory (Lindbeck and Snower, 1990). According to efficiency wage models, higher than competitive wages are consistent with firms' profit maximization under different forms of imperfect information which may depend on industry-specific characteristics. According to the insider-outsider theory, wages are higher in industries where firms stand to lose more from a breakdown of wage negotiations, that is where profits are larger, capital-labour ratios are greater, concentration ratios in the product markets are higher, and insiders' power is stronger possibly on account of a higher degree of unionization and a heavier coverage by job security legislation.

Efficiency wage and insider-outsider theories are usually seen as rival explanations of the existence of wages above the market clearing level (Lindbeck and Snower, 1987). A discrimination between the two theories in the context of the empirical evidence for inter-industry wage differentials is difficult, because both predict their existence. Industry differentials are just an indirect consequence of efficiency wage and insider-outsider forces. More direct tests have been attempted for both theories independently, using firm level data (Wadhwani and Wall, 1988; Nickell and Wadhwani, 1988; Nickell and Wadhwani, 1990). Evidence from these studies is inconclusive, in the sense that both theories seem to receive substantial support within the same country (the U.K.). A direct approach that encompasses both efficiency wage and insider-outsider factors and permits to discriminate between the two alternative explanations still remains unexplored.

A better understanding of the relative importance of efficiency wage and insider-outsider considerations can be achieved by considering inter-industry wage differentials in a wider conceptual perspective. Efficiency wage and insider-outsider forces can be seen as acting with different intensity according to the institutional framework characterizing the way in which the labour market operates.

In centralized labour markets firms cannot set wages unilaterally, as implied by the efficiency wage theory (Krueger and Summers, 1988). Instead, wages are typically the
outcome of a bargaining process. A certain degree of centralization of wage bargaining might reinforce insider-outsider effects. Turnover costs are generally raised by a high degree of unionization, job protection and other factors positively correlated with the degree of centralization. Although the insider-outsider model does not necessarily imply the existence of unions or collective bargaining, one of the channels through which wages might be set above the market clearing level is the effect of insiders' market power, which is likely to be greater the higher the degree of unionization and legal job protection (Lindbeck and Snower, 1990). If centralization of wage bargaining is at an industry level, this might be reflected in significant inter-industry wage differentials: wages will be higher in more unionized industries and lower in less unionized ones (Lindbeck and Snower, 1990).

In decentralized labour markets firms can set wages almost unilaterally. If there is any rationale for them to pay wage premia they may do so. Typically efficiency wages are most likely to be paid where workers are most likely to be motivated by external discipline (Shapiro and Stiglitz, 1984), i.e. where workers are less unionized and protected, which are characteristics associated with decentralized wage bargaining. If unions and job security legislation can protect workers from the risk of a potential job loss - by making dismissals more difficult and/or costly - firms would have no reason to pay efficiency wages. The degree of imperfect monitoring of workers' effort on the job may then depend on industry-specific conditions and be reflected in significant inter-industry wage differentials.

It is worth noting, however, that in rigorous terms none of these basic conditions is either necessary or sufficient to favour one of the two theories rather than the other or indeed to favour any of them at all. Inter-industry wage differentials remain essentially consistent with both theories, but in fact are not necessarily implied by them. A possible strategy is to examine a sufficiently large variety of different institutional contexts in a multi-country study, in order to gain some insight about whether and where inter-industry wage differentials may exist. If industry differentials are substantial in decentralized labour markets, this may be consistent with the efficiency wage hypothesis. If industry differences are substantial in centralized labour markets, this could be explained in the context of the insider-outsider theory. In both cases though alternative explanations cannot be totally ruled out. If industry differentials are substantial independently of the institutional setting, then labour market institutions might not play any role in the process of wage determination.
This thesis adds some pieces of empirical evidence to the puzzle of inter-industry wage differentials, according to analytical framework discussed above. The various problems arising from this kind of microeconometric analysis of industry differentials are far from being completely solved, the most relevant of which probably remains the unobservable labour quality objection. However, new, additional evidence, especially in the multi-country perspective presented and discussed here, helps to shed some light on the inter-industry wage differentials anomaly.

Chapter 2 reviews the theoretical framework for the measurement of inter-industry wage differentials. The Chapter provides a summary of the main features of alternative theories of the labour market and a study of their analytical and empirical implications with respect to the inter-industry wage structure. Among competitive theories of the labour market, I examine the human capital theory and the theory of compensating differentials. Among non-competitive theories of wage determination, efficiency wage models and the insider-outsider model are illustrated. I then give a detailed description of the empirical aspects of the various theories in terms of inter-industry wage differentials, explaining how alternative hypotheses about the nature of industry differences are usually tested in econometric studies. The main results emerging from the empirical literature on inter-industry wage differentials are also presented and evaluated.

Moving into a broader, multi-country perspective of the debate, I then discuss the possible effects on the structure of relative wages of different institutional conditions characterizing the labour market, with particular attention to the degree of centralization of wage bargaining. Finally, I present a brief description of the institutional conditions for wage bargaining in the seven countries considered in the empirical studies of the following Chapters: the United States, Canada, Australia, Germany, the Netherlands, Austria and Sweden. These countries span a wide range of different institutional settings among OECD labour markets. The analysis refers to the situation characterizing these countries in the mid-1980s, the period of reference in my later econometric estimates.

Chapter 3 considers some preliminary empirical evidence for inter-industry wage differentials based on aggregate average industry wage data, as it emerges from studies provided by various authors. One of the findings which is often put forward as supportive of non-competitive explanations for industry wage differences is the stability over time and across countries of wage structures measured by means of this type of aggregate data. I show
and discuss some of the results presented in two recent articles on aggregate inter-industry wage differentials, the first by Krueger and Summers (1987) and the second by Gittleman and Wolff (1993). The authors, for their comparisons of industry wage structures over time and across countries, rely on three different measures of association: the Pearson product-moment correlation coefficient, the Spearman rank correlation coefficient, and the coefficient of concordance. The statistical properties of the sampling distributions of these three statistics are not totally obvious and only occasionally taken into account in economic applications. A clear understanding of these properties is especially important in the treatment of small samples, which is the situation faced by Krueger and Summers and by Gittleman and Wolff in most cases, as well as a recurring characteristic of the analyses presented in the following Chapters of the thesis.

Chapter 3 carefully evaluates the three metrics in terms of their statistical properties. These properties are then applied to test the statistical significance of the findings presented by Krueger and Summers and by Gittleman and Wolff for inter-industry wage differentials. I provide a complete and thorough evaluation of all the results presented in the two quoted articles, clearly specifying the methodology used in each case, stating explicitly the suitable null and alternative hypotheses, and setting appropriate significance levels for the various tests. Both the studies considered here reach the conclusion that inter-industry wage structures are characterized by a high degree of stability over time and are highly similar across countries. Such a regular pattern seems to be explicable only by introducing non-competitive considerations and seems to deny any role of institutional or other country and time specific factors influencing the process of wage determination. This result is challenged from two points of view. The first is the reliability and the actual statistical significance of the values obtained for the various measures of association used to judge the degree of stability of industry wage differentials. The second, and more relevant, is the overall appropriateness of aggregate wage data - as compared with micro data - as a basis for inter-temporal and cross-country comparisons of industry wage structures.

Chapter 4 starts considering empirical evidence for inter-industry wage differentials in Germany based on micro data. Empirical analyses of the determinants of industry wage differentials using individual data were first provided for the U.S. labour market. According to these studies, industry wage differences appear to remain substantial even after controlling for a variety of human capital factors and working conditions. These results have been
regarded as strongly supportive of non-competitive theories of wage determination like efficiency wage and insider-outsider theories. After Krueger and Summers's (1988) seminal article, further evidence based on a very similar approach has become available for some other countries: Australia, Austria and Sweden. Even if some of the authors tend to concentrate more on the similarities rather than the dissimilarities between the U.S. and these other countries, their results are not totally unambiguous. Clear differences among countries in terms of size, statistical significance and variability inter-industry wage differentials seem to emerge.

Chapter 4 presents evidence for Germany based on a cross-section of individual data available from the first wave (1984) of the German Socio-Economic Panel (SOEP). The approach here adopted is also similar to Krueger and Summers's and essentially consists in the estimation with cross-sectional data of a wage equation which includes measures of human capital and working conditions, as well as industry affiliation controls, as explanatory variables. This method permits an evaluation of competitive and non-competitive influences on the process of wage determination and the resulting inter-industry structure of wage differentials. My empirical analysis of the German case, however, differs from Krueger and Summers's study in a number of methodological aspects. The most relevant of these is the use of a different estimation technique, the Heckman's two-stage model for sample selection bias, rather than a simple OLS regression. This choice is induced by a feature specific to the German data-set and the way it records information about individual wages and working hours. In the attempt to define a dependent hourly wage variable for my model as accurate as possible, a potential problem of sample selection bias arises due to the exclusion of overtime workers.

In Chapter 4 I also consider cross-country comparisons of inter-industry wage structures as emerging from micro data, rather than from average industry data. I compare my results for Germany with those presented in other four studies: for the U.S. by Krueger and Summers (1988); for Australia by Borland and Suen (1990); for Austria by Winter-Ebmer (1992); and for Sweden by Edin and Zetterberg (1992). My interest in comparing the wage dispersion across industries in these five countries derives from the fact that they are usually considered as spanning a wide range of different labour market institutional structures and, in particular, of different degrees of centralization of wage bargaining. Through these
comparisons I can therefore achieve a better understanding of the relationship between institutional conditions of wage bargaining and inter-industry wage dispersion.

Chapter 5 provides additional evidence concerning the issue of inter-industry wage differentials in an international perspective. The empirical analysis proposed here relies on an approach which is different from that adopted in Chapter 4 and which tries to overcome some of the difficulties met in that context when performing cross-country comparisons. For this purpose I employ a different data source, the "Luxembourg Income Study" (LIS) data-bank, and directly estimate cross-sectional evidence for five different countries: the United States, Canada, Australia, Germany and the Netherlands. Inter-country comparisons based on studies made by various authors confront certain limitations. The degree of comparability of the results is affected by several differences in the definition of the samples of interest and of the dependent and explanatory variables, as well as in the statistical methodology applied for the estimation of the models. Moreover, the comparisons are made essentially through simple correlations between the vectors of estimated wage differentials appearing in the various papers, aggregated for this purpose into a common set of industries. Little information is usually provided about various aspects of the estimation procedure and the reader has no access to some of the statistical results. This, as a matter of fact, limits the possibility of a statistical comparison between estimated inter-industry wage structures to the calculation of correlation coefficients.

The empirical analysis in Chapter 5 employs a different strategy. The LIS data-bank is a collection of cross-sectional micro data-sets for several countries that can be accessed through the electronic mail system and processed with the statistical package SPSS-X. The use of a single data source for various national data-sets partly reduces the above-mentioned problems of heterogeneity, because it permits, to a certain extent, a control of the differences affecting the reliability of cross-country comparisons. Besides, the direct estimate of the wage regression models for the different countries gives the possibility of employing all the statistical results produced by the estimation procedure. In particular, the availability of the variance-covariance matrices of estimated coefficients permits the construction of a test for cross-country equality restrictions on inter-industry wage structures. This test, based on the method of minimum distance estimation, provides a criterion to evaluate the hypothesis of similarity among countries which is an alternative to simple correlation coefficients. The minimum distance $\chi^2$ test makes recognition of the fact that inter-industry wage differentials
for each country are only estimates of the true population parameters, subject to a sampling error. They are therefore associated with measures of the precision of the estimates which are otherwise ignored in the calculation of correlation coefficients.

The nature of the data source, the desire to examine various countries, and the necessity to obtain sufficiently comparable results, however, make the approach adopted in Chapter 5 less accurate than the one used in the analysis of the German case and in the other studies considered in Chapter 4. In this respect, the estimates obtained in Chapter 4 are more satisfactory and, therefore, should be evaluated together with the results given in Chapter 5.

Chapter 6 summarizes the main results of the previous Chapters, proposes some general conclusions about the nature of the empirical findings of the thesis, and suggests a possible direction for further developments in the study of inter-industry wage differentials.

Finally, the Appendix tackles an econometric problem that arises at various stages in the preceding Chapters. In the empirical literature on inter-industry wage differentials, the standard procedure is to express such differentials in normalized form, as deviations from the employment-weighted mean differential, following the procedure suggested by Krueger and Summers (1988). Since Krueger and Summers' article, nearly every study of the inter-industry wage structure has adopted the same approach. This simple algebraic transformation of estimated industry coefficients presents a double advantage. Firstly, wage differentials are "normalized", in the sense that they express wage differences in percentage points with respect to the average employee in the whole economy, rather than relative to some arbitrary group of employees. The resulting differentials are therefore more easily interpretable. Secondly, wage differentials become independent of the arbitrarily chosen base industry - the omitted industry dummy - and therefore they can be directly compared across studies using different industries as reference groups.

The case of inter-industry wage differentials is just an example of a more general econometric issue, the existence of alternative ways to parameterize a model which includes dummy variables among the regressors. In the Appendix I show how estimated industry dummy coefficients and wage differentials normalized à la Krueger and Summers correspond to the parameters of two alternative specifications of the same theoretical model. In particular, the usually estimated wage regressions represent a specific parameterization of such a model, while wage differentials as deviations from the (weighted) mean differential actually derive from a more general parameterization of the same model.
The Appendix illustrates the relationships between all the possible, alternative parameterizations of a dummy variable model and provides formulae to switch from one parameterization to another without actually re-estimating the model. Moreover, it presents algorithms to transform accordingly the variance-covariance matrix of the estimated parameters, so that inference procedures can be established in each case. This last point has been neglected by Krueger and Summers and many other authors, who, after having applied the normalization of industry differentials in deviation form, rely on simple, unadjusted OLS standard errors for their inference procedures. This approach essentially implies the use of the standard errors estimated from a specific model to construct $t$-tests for the parameters of the general model. In principle, the procedure is incorrect and, in practice, it may give rise to differences in the evaluation of the statistical significance of single normalized differentials which are of considerable size.
References


Chapter 2

Theoretical Framework and the Measurement of Inter-Industry Wage Differentials

2.1 Introduction

As early as the 1940-50s, economists started looking at inter-industry wage differentials as an anomalous empirical result that needed a rationalization in the context of a theory of wage determination (Lebergott, 1947; Slichter, 1950). Since then a number of possible explanations have been proposed.

Competitive theories of the labour market suggest that observed inter-industry wage differentials are not an anomaly at all. Job characteristics which have no direct influence on the utility of workers should not affect the level of wages. Workers are paid a wage equal to their opportunity cost, which depends on accumulated human capital and their working conditions. In other words, equally skilled workers should be compensated in a way that guarantees equal levels of utility. In this context, inter-industry wage differentials might simply reflect labour quality differences which vary systematically across industries and/or compensating differentials for some aspects of the working conditions in the various industries of employment.

Non-competitive theories, instead, predict that job attributes having no effect on workers' utility should systematically affect the wage structure, as far as they have an influence on the optimal solution to the firms' maximization problem. Equally skilled workers are paid differently according to features like industry affiliation. Possible explanations for persistent inter-industry wage differentials for equally productive workers in the class of
non-competitive theories are offered by efficiency wage models (Krueger and Summers, 1988) and the insider-outsider model (Lindbeck and Snower, 1990).

Recent literature has also suggested a more general explanation for the observed pattern of inter-industry wage differentials, based on the relationship between the degree of wage dispersion across industries and the type of labour market institutions (Bell and Freeman, 1987; Freeman, 1988; Rowthorn, 1992). Labour market institutions have received increasing attention as a determinant of the labour market performance of the advanced economies in terms of employment and unemployment rates and, more generally, of the macroeconomic performance of a country (Paloheimo, 1984; Bruno and Sachs, 1985; Ch. 11: Newell and Symons, 1987; Calmfors and Driffill, 1988; Freeman, 1988; Solow, 1990; Soskice, 1990; Layard et al., 1991; North, 1991; Pekkarinen, Pohjola and Rowthorn, 1992; Freeman, 1993a and 1993b; Hartog and Theeuwes, 1993). Among the aspects characterizing the structure of labour markets, the focus is on the degree of centralization of wage bargaining. Countries with very high or very low inter-industry wage dispersion are supposed to be the countries with highly decentralized or highly centralized wage setting procedures respectively, while intermediate degrees of centralization tend to be associated with an intermediate wage dispersion across industries (Freeman, 1988).

In the vast empirical literature on inter-industry wage differentials, the phenomenon has been analysed from three complementary points of view: the existence and importance of industry differentials in an observed year in a given country; their persistence over time; and their similarity across countries. All three approaches involve rather complex measurement problems. As we will see in the rest of this Chapter (and in fact of the entire thesis), even the pure existence of significant inter-industry wage differentials at any one point in time in a certain country is not trivial to be demonstrated. Stability of industry differentials over time and across countries is even more difficult to assess in rigorous statistical terms.

Researchers have essentially used three different empirical strategies - or a combination of them - to address the issue of measurement of inter-industry wage structures. The first consists simply in taking an average wage for each industry from aggregate industry data sources such as OECD or ILO publications. The second relies instead on individual data and consists in estimating "raw" industry wage differentials from a regression of some (log) wage measure on a set of industry dummy variables. The third is an extension of the second, which includes a host of individual characteristics among the regressors such as age,
education, occupation, race, marital status and so on. In other words, the third strategy consists in estimating an earnings function of human capital theory enriched with a set of industry dummy variables. A number of early studies (Lebergott, 1947; Slichter, 1950; Dunlop and Rothbaum, 1955; Lewis, 1963), as well as more recent ones (Papola and Bharadwaj, 1970; Lawson, 1982; Tarling and Wilkinson, 1982; Krueger and Summers, 1987; Freeman, 1988; Gittleman and Wolff, 1993), have used the first of these measurement methods. The second method has been employed by some authors (Dickens and Katz, 1987a and 1987b; Krueger and Summers, 1987; Katz and Summers, 1989; Edin and Zetterberg, 1992) either in conjunction with the first or as a term of comparison with the third.

In the following Chapters I will consider all three measurement methods, mainly to appraise results already provided by the existing literature. But the third method of measuring inter-industry wage differentials is the only one that, to a certain extent, allows to evaluate differentials of a competitive or non-competitive nature and discriminate among alternative theories. Even with the third most statistically rigorous method, in fact, we face some serious limitations which will be illustrated in the rest of this Chapter. However, it certainly represents a better empirical strategy if compared with the other two commonly used in the literature. This point will be discussed in detail in Chapter 3.

The existence of significant industry wage differentials at any one time in a given country, their persistence over time, and their similarity across countries are three complementary aspects of the same anomaly, but can be - and have been - analysed in order to test different theoretical hypotheses. The ability of different labour market theories to account for the three aspects, in fact, varies.

In what are considered seminal papers in the field of inter-industry wage differentials (Dickens and Katz, 1987a; Krueger and Summers, 1987 and 1988), the authors show their existence for one year (1983 or 1984)\(^1\) in one country (the U.S.) and suggest efficiency wage models as the most plausible rationalization. All papers apply the third most rigorous measurement method: a data set with observations at the individual level (CPS) and a regression of the (log) wage rate on individual characteristics and industry dummy variables. In this context, significant industry differentials are consistent with the efficiency wage

\(^1\) Actually, Krueger and Summers (1988) estimate inter-industry wage differentials also for 1974 and 1979, but the main emphasis is definitely on the 1984 results. In their paper they devote only some 20 lines to the issue of persistence over time. I will return in the issue of persistence later in this Section.
hypothesis. Nevertheless, their existence per se is - strictly speaking - neither a necessary nor a sufficient condition for efficiency wages to be a valid theory of wage determination. It is not necessary because efficiency wage considerations could operate at a level different from the industry level. For example, they could generate significant intra-industry relative wage premia at the firm level, but cancel out when aggregating firms into industries. Although perhaps not very likely, this possibility cannot be excluded in principle. It is not sufficient because significant industry differentials are consistent with rival explanations, other theories of wage determination that also predict their existence and cannot be ruled out.

One such rival explanation is the insider-outsider theory (Lindbeck and Snower, 1990). The existence of significant inter-industry wage differentials observed at any one point in time in a given country is also consistent with the insider-outsider hypothesis. However, the kind of criticism raised about the relationship between industry wage differentials and the efficiency wage theory also applies here. Industry differentials are neither necessary nor sufficient for regarding the insider-outsider model as a plausible theory of wage determination. Insider forces might in fact operate at a level other than the industry level and observed industry wage differentials could be consistent with alternative theoretical explanations, in particular the efficiency wage hypothesis. Efficiency wage and insider-outsider theories are seen as rival explanations of the existence of wage premia (Lindbeck and Snower, 1987a), but a discrimination between the two theories in the context of observed inter-industry wage differentials is difficult because both predict their existence. Lindbeck and Snower (1990) do not provide any direct empirical evidence in support of their model, but in their theoretical rationalization of industry wage differentials in terms of the insider-outsider approach they suggest, implicitly, a possible way to discriminate between the two theories (see Sections 2.3 and 2.4 for further details). However, the empirical implementation of such a test meets with serious limitations both in terms of availability of data and appropriate econometric techniques.

The rival explanation par excellence of all non-competitive theories is the competitive theory of wage determination. According to the competitive approach, the existence of significant inter-industry wage differentials at any time and in any country just reflects a problem of unobservable labour quality and/or working conditions "picked up" by industry differentials. If this problem could be solved with appropriate techniques, industry wage
differentials would not be observed at all. This point will be fully discussed in Sections 2.2 and 2.4.

Let us turn to the second aspect of the inter-industry wage differentials anomaly, their persistence over time. Some authors (Dickens and Katz, 1987a and 1987b: Krueger and Summers, 1987 and 1988) put forward this stylized fact in order to provide stronger evidence in support of efficiency wage models and against alternative competitive rationalizations. The fact that industry differentials not only exist in a country (the U.S.) in a certain year, but are also persistent seems to these authors a strong point in favour of the generality of the efficiency wage theory. These studies of the persistence aspect rely either on average industry wages from aggregate data sources (Dickens and Katz, 1987a and 1987b; Krueger and Summers, 1987) or on individual data and a regression approach (Krueger and Summers, 1988) and persistence is essentially evaluated by calculating simple correlations between industry wage structures across years.

This kind of persistence of observed inter-industry wage differentials - like their existence - seems neither a necessary nor a sufficient condition for efficiency wages to be a plausible theory of wage determination. Technology, forms of social and economic organization, and in general the structure of (asymmetric) information may well change over a period of time as long as the one considered by some authors (for example, 84 years). This just implies that the inter-industry structure of wage differentials might also change and correlations over long periods of time might result low. In my view, this does not necessarily mean that the efficiency wage theory is a less powerful explanation of the existence of inter-industry wage differentials where and when they are actually observed. Also, persistence per se does not rule out alternative rationalizations such as the insider-outsider theory or even the competitive theory of unobservable labour quality. However, Krueger and Summers (1987) consider another interesting aspect of persistence over time. Among other things, they want to test the efficiency wage hypothesis against the alternative hypothesis that the observed evolution of inter-industry wage differentials just reflects changes in labour market institutions. Consequently, they interpret their evidence as supportive of efficiency wages and against the alternative, since institutional conditions have certainly changed during the period they observe (1900-1984) while the structure of industry wage differentials has (apparently) remained remarkably stable.
Unfortunately, given the cross-sectional nature of the available data, I will not be able to address rigorously the issue of persistence over time in this thesis. The next Chapter 3 will be partly devoted to an assessment of existing evidence about persistence. However, the focus will be on the measurement method most commonly used in the literature (correlations based on average industry wages from aggregate data sources), rather than on the relationship between the aspect of persistence and alternative theories of wage determination. The role of labour market institutions in explaining the inter-industry wage differentials anomaly is however worth careful consideration. This can be done in the context of the third aspect of the anomaly, the similarity of differentials across countries.

Krueger and Summers (1987) present some evidence of strong similarity of inter-industry wage differentials across a large number of countries and interpret their results as supportive of the generality of the efficiency wage hypothesis. This study relies exclusively on average industry wages from aggregate data sources and simple correlations of industry wage structures between pairs of countries. As in the case of persistence over time, the similarity of industry differentials across countries is neither a necessary nor a sufficient condition for regarding efficiency wage models as a valid rationalization of such differentials where they are actually observed. In particular, we are unable to rule out the insider-outsider theory or the competitive theory of unobservable labour quality as possible alternative explanations. Again, Krueger and Summers consider in particular labour market institutions as an alternative to efficiency wages to account for the observed pattern of inter-industry wage differentials across countries. And, again, they conclude rejecting institutional conditions as a possible explanation, given that labour market institutional settings vary widely across the countries considered in their analysis while the structure of industry wages appears to remain stable.

The similarity of inter-industry wage differentials across countries and its relationship with labour market institutions - in particular, the degree of centralization of wage bargaining - is an aspect of the anomaly that I can analyse with the data available to me. As mentioned above, Krueger and Summers derive their conclusion about cross-country similarities using average industry wages from aggregate data sources. But is this result confirmed when inter-industry wage differentials are estimated from individual data in a regression approach which takes into account differences in individual characteristics? Chapters 4 and 5 will analyse the
two aspects of existence and similarity of industry differentials across a variety of countries following this measurement method.

In the rest of this Chapter I will present in greater detail the various alternative theories that have been proposed in the literature to rationalize the inter-industry wage differentials anomaly. I will also illustrate the various aspects and problems of their measurement, starting from the background of earnings functions of human capital theory. Section 2.2 illustrates, among competitive theories of the labour market, the human capital theory and the theory of compensating differentials. Section 2.3 presents, among non-competitive theories of wage determination, efficiency wage models and the insider-outsider model. Section 2.4 describes in detail the empirical aspects of the various theories proposed in terms of inter-industry wage differentials, explaining how - and with what outcomes - alternative hypotheses about the nature of industry differences are usually tested in econometric studies. Section 2.5 discusses the possible effects on the structure of relative wages of different institutional conditions in the labour market, with particular attention to the degree of centralization of wage bargaining. Section 2.6 briefly summarizes and compares the institutional conditions for wage bargaining in the seven countries considered in the empirical analyses of the following Chapters: the United States, Canada, Australia, Germany, the Netherlands, Austria and Sweden. These countries span a wide range of different institutional settings among OECD labour markets. Section 2.7 contains some concluding remarks.

2.2 Competitive Theories: Human Capital Theory and the Theory of Compensating Differentials

The human capital theory of wage determination has produced a vast literature investigating the importance of investment in human capital as an explanation for various types of wage differentials, among which inter-industry wage differentials are one of the possible aspects. From the theory of human capital, earnings functions have been originally developed as an empirical tool to study the effects of investment in schooling and on-the-job training on the pattern of life cycle earnings (Mincer, 1958, 1962, 1974; Becker, 1975; Becker and Chiswick, 1966). Subsequently, even in recent years, earnings functions have been
extensively used as an important theoretical and statistical basis also for studying other wage determinants and to test rival theories of wage determination.

Mincer's (1958) derivation of earnings functions starts from a simple idea, which goes back to Adam Smith's theory of equalizing differences (Smith, 1776) and to Friedman and Kuznets's (1947) empirical study of income differences among independent professionals. Additional schooling entails opportunity-costs in the form of foregone income at the beginning of working life and therefore must be compensated by higher lifetime earnings. The value of additional schooling can be thought as the expected present value of future earnings to which it gives rise. In considering the decision to continue schooling, each person equals future earnings with the opportunity-costs of schooling and if different jobs require different schooling investments, this condition must hold for each schooling level. In a long-run competitive equilibrium, hence, labour supply at each schooling level is infinitely elastic at the wage that compensates for schooling undertaken, labour supply and demand for each schooling level are equated and labour demand determines the number of workers who can choose each job (but not the wage they are paid), and no workers desire to change their schooling level.

Human capital theory thus formulated relies on a set of strong assumptions. First, as we have seen, the labour market is assumed to be perfectly competitive. Second, all individuals are supposed to have identical initial endowments in terms of intelligence, physical capacities, family background or any other environmental condition. Third, capital markets are assumed equally accessible to every individual. In its simplest form - as originally developed by Mincer (1958) and Becker (1975) - human capital theory also requires a further series of simplifying assumptions: the only form of investment in human capital is education, so this investment necessarily implies a postponement of entry into the labour force; working life has the same length for every individual, so individuals undergoing longer education will retire later (and no individual will die before retirement); the only cost of education is forgone income; and the only benefit from education is in terms of higher future income.

In this framework, the simplest human capital model of educational choice can be formalized as follows. The decision to undergo education involves borrowing to finance it at a constant interest rate $r$. Let $w(s)$ represent the average annual earnings of a person that chooses to remain in school for $s$ years and $w_0$ the average annual earnings of a person with
zero years of schooling (i.e., the average annual earnings received if the person enters immediately the labour market). If $W(s)$ is the human capital wealth associated with the schooling decision point $s$, then the value of human capital wealth, evaluated at the age of school entry, is:

$$W(s) = \frac{w(s) e^{-rs}}{r},$$

where $w(s) e^{-rs}$ is the present value of future income associated with the schooling decision point $s$.

The problem of optimal schooling decision amounts to choosing $s$ to maximize $W(s)$. The first-order condition for maximizing $W(s)$ with respect to $s$ results in the "harvesting condition":

$$\frac{d \ln w(s)}{ds} = r.$$  \hspace{1cm} (2.2)

This first-order condition admits of an easy economic interpretation: the rate of growth of the value of future income (left-hand expression) must be equal, for any schooling decisions, to the rate of growth of present income opportunities foregone - the opportunity-cost of schooling (right-hand expression).

Market equilibrium supply of workers by schooling years implies equal human capital wealth for all schooling groups:

$$W(s) = W_0 = \frac{w_0}{r}, \quad \text{for all } s,$$  \hspace{1cm} (2.3)
where \( W_0 \), the human capital wealth associated with the decision of zero schooling, is a constant given that all individuals are assumed initially identical. Substituting (2.3) into (2.1), we obtain:

\[
w(s) = w_0 e^{rs},
\]

(2.4)

and taking the natural log of both sides of (2.4):

\[
\ln w(s) = \ln w_0 + rs.
\]

(2.5)

Equation (2.5) represents the simplest form of a so-called "Mincer earnings equation". The constant term is the log of the income equivalent of initial human capital value and the parameter \( r \) measures (from the first-order condition (2.2)) the marginal internal rate of return on schooling investments.

Extensions of the simplest earnings function have been developed to take into account other possible implications of the human capital theory of earnings. A major innovation has been introduced by Mincer (1974), using and extending Becker's (1962) and Becker and Chiswick's (1966) analysis of life cycle variations in earnings. This extension essentially implies to relax the assumption that the only form of investment in human capital is education. Over the life cycle, earnings exhibit empirically an increasing, concave path with respect to age - the so-called "age-earnings profile". Mincer interprets this effect of age in terms of labour market experience, which implies a certain amount of explicit and implicit on-the-job training. If on-the-job training is general, the individual faces its opportunity-cost in the form of lower income at the beginning of working life and is compensated by higher expected future earnings. And if log-earnings profiles with respect to experience of different schooling groups are approximately parallel (in other words, if it can be assumed that a given
increment of schooling has the same proportional effect on earnings at any level of experience), the earnings function (2.4) can be rewritten in the weakly separable form:

\[ w(s,x) = w_0 e^{r s} e^{(q k_0 + q k_1 + \ldots + q k_x - k_x)} , \] (2.6)

where \( x \) measures the length of labour force experience, \( q \) is the rate of return to on-the-job training and \( k_j \), for \( j = 0, \ldots, x \), is the fraction of earnings foregone in the \( j \)-th year of experience (Psacharopoulos and Layard, 1979).

Log-linearising equation (2.6), we obtain:

\[ \ln w(s,x) = \ln w_0 + r s + \sum_{j=0}^{x-1} (q k_j) - k_x . \] (2.7)

It is generally assumed (Mincer, 1974) that investment in on-the-job training declines linearly with years of experience \( x \), so that:

\[ k_x = k_0 - c x , \] (2.8)

where \( k_0 \) and \( c \) are constants. So, substituting (2.8) into (2.7) and integrating:

\[ \ln w(s,x) = \ln w_0 - k_0 + r s + (q k_0 + c + \frac{1}{2} q c) x - \frac{1}{2} q c x^2 \]

\[ = \ln w_0 - k_0 + r s + a x + b x^2 , \] (2.9)
where \( a = qk_0 + q + \frac{1}{2} qc \) and \( b = -\frac{1}{2} qc \). Earnings functions (2.5) and (2.9) may be interpreted as hedonic price functions in the sense of Rosen (1974), which reflect the equilibrium of the supply and demand for workers at each level of schooling and experience.

Subsequent literature has also extensively considered other factors that may have an influence on individuals' earnings either directly or, indirectly, by affecting the rates of return to education and the schooling decision. Various studies have concentrated on the severe assumptions underlying previous formulations of human capital theory and regarded them as rather unrealistic. Considerable investigation has gone especially into the effects of imperfect capital markets, family background and innate ability (Atkinson, 1983). Imperfections in capital markets are likely to have an impact on investment in human capital by raising the marginal cost of borrowing for all individuals and by offering different borrowing conditions to different individuals. Differences in access to borrowing are hence reflected in differences in access to education (Becker, 1967). Family background conditions may operate directly on earnings, by affecting opportunities of access to better paid jobs, or indirectly via education, by influencing motivation and - more important - by altering the family budget constraint to its financing (Bowles, 1972). Unequal abilities, in terms of both physical and intellectual characteristics, are also believed to be related to differences in earnings. The relationship is again both direct and indirect through education. Given a certain level of education, a higher ability may increase earnings of an individual by improving directly his/her productive capacity. Ability also interacts with education by affecting the opportunity of access to selective educational institutions, so that individuals with higher ability may receive more - and possibly better - education and hence higher earnings. Moreover, a higher ability may increase the rate of return to each year of schooling. It has in fact been assumed that ability and education are complementary (Becker, 1976), so that the effect of education on earnings is higher for individuals with higher ability. The assumption of no interaction between education and post-school on-the-job training (parallel log-earnings profiles with respect to experience for all schooling groups) has also been criticized (Psacharopoulos and Layard, 1979). The amount of post-school investment in training and its profitability may in fact be influenced by previous educational choices.

In this theoretical framework, individuals are supposed to differ by schooling and experience levels, but are assumed to be otherwise observationally identical (after controlling
for ability and family background). This represents a significant limitation of the theory. In order to explain wage differentials, it is necessary to specify how variations in earnings are divided between variations in hours of work and variations in hourly wages. If we follow the convention of the earnings function literature which assumes that the life cycle pattern of hours of work is exogenously fixed and neglect labour supply considerations, we introduce an untenable assumption when considering the returns to human capital investment for women, because of their substantial commitment to non-market household activities and the high degree of variability of their labour market participation over the life cycle (Willis, 1986). It is therefore advisable to regard the theoretical discussion in this Chapter as confined to male workers only. The empirical analyses in the following Chapters also conform to this restriction, whenever possible.

In the context of human capital theory, any wage differential - and in particular inter-industry differences - is therefore supposed to reflect exclusively a difference in labour quality, measured in terms of schooling and working experience levels (after correcting for exogenous characteristics, ability inequalities and family conditions). This implies that if inter-industry wage differentials are empirically observed, they must be due to a systematic distribution of workers of different quality and productivity across industries.

Also in the class of competitive theories of the labour market and as an extension of the human capital approach, the theory of compensating differentials provides a more complete model of wage determination. It also rests on Adam Smith’s theory of equalizing differences (Smith, 1776) and on the theory of hedonic prices (Rosen, 1974), and takes human capital earnings functions as a basis for the development of a more sophisticated earnings model. The idea behind the model is that workers with given human capital characteristics may choose among jobs paying different wages and with differing nonwage attributes. In order to attract workers of a given quality, employers offering jobs characterized by worse working conditions must pay higher wages that employers offering jobs with more pleasant nonwage attributes. In labour market equilibrium, individuals face a set of combinations of wage and working conditions and are assumed to choose among these opportunities in order to maximize their utility.

If the trade-off between wages and working conditions is supposed to hold in the same way for all workers with similar human capital characteristics, the model of wage determination could be derived by simply augmenting a standard human capital earnings
function with variables which represent working conditions aspects, in a weakly separable form (Duncan and Holmlund, 1983). Equation (2.6) could then be rewritten as:

$$w(s,x,y) = w_0 e^{rs + q_k y} f(y),$$

where $y$ is a vector of measures of working conditions. However, since theory does not provide clear indications about the functional form of $w(s,x,y)$ when some function $f(.)$ of working conditions is included, the model is usually derived, on empirical grounds, as a mixed log-linear and additive version of equation (2.10) (Brown, 1980; Duncan and Holmlund, 1983):

$$\ln w(s,x,y) = \ln w_0 + rs + ax + bx^2 + g^T y$$

In the framework of the theory of compensating differentials, inter-industry wage differences among workers of the same quality are then assumed to reflect exclusively differences in some aspects of the working conditions that are typically associated with the various industries of employment. Productive sectors characterized by more dangerous or unpleasant jobs will tend to pay higher wages for a given quality of labour, while sectors with more desirable working conditions will be able to attract labour of the same quality even if paying lower wages.

2 In practice, measures of working conditions are usually represented by binary zero-one qualitative variables or by discrete and arbitrarily truncated variables, referring to some scale which quantifies job characteristics such as the degree of dangerousness, the intensity of stress, etc. A fully log-linear specification would imply squared values of these measures on the right-hand-side of equation (2.11), which under these circumstances are meaningless.
2.3 Non-Competitive Theories: Efficiency Wage Models and Insider-Outsider Theory

In the class of non-competitive theories of the labour market, efficiency wage and insiders-outsiders models have been developed in recent literature as providing coherent microfoundations for involuntary unemployment and wage rigidity. The two theories suggest alternative microeconomic rationales for macroeconomic models of unemployment in a regime characterized by excess supply of labour and equilibrium in the goods market. In other words, they provide explanations for the failure of the labour market to clear which do not depend on the fact that the product market does not clear. According to the disequilibrium models of Barro and Grossman (1976) and Malinvaud (1977), efficiency wage and insiders-outsiders theories refer to a regime which is on the boundary between the Keynesian and the Classical regimes. A vast literature has been produced in recent years that analyses the various aspects of efficiency wage and insider-outsider theories (Akerlof and Yellen, 1986; Katz, 1986; Stiglitz, 1986; Lindbeck and Snower, 1988c; just to mention a few examples). In this Section I will consider only some of the features of the two theories which are directly related to the problem of measurement and interpretation of inter-industry wage differentials in an empirical approach.

In the efficiency wage theories the source of involuntary unemployment is essentially firms' imperfect information about the productivity of their employees. Imperfect monitoring of workers' performances leads to a behaviour which can be explained in terms of bounded rationality (Simon, 1979). Besides, firms are assumed to make both wage and employment decisions unilaterally, so that they may use the wage as a screening device for productivity. Starting from these assumptions, we can divide the efficiency wage theories into two categories: adverse selection and moral hazard approaches. In the adverse selection approach, production characteristics (workers' productivity) are imperfectly monitored: in the "productivity differential model" (Malcomson, 1981), firms attract higher unobservable quality workers by offering higher wages; in the "turnover model" (Stiglitz, 1974; Salop, 1979), firms induce workers to stay with the firm by offering higher wages, thus reducing quit-associated costs. In the moral hazard approach, activities of agents (workers' effort on the job) are imperfectly monitored: in the "shirking model" (Calvo and Wellisz, 1978; Shapiro and Stiglitz, 1984), firms reduce workers' shirking by increasing the wage and thus raising the cost of potential job loss; in the "on-the-job search model" (Snower, 1983), firms increase
their wage offers in order to prevent search activities which reduce workers' effort; in the "sociological model" (Akerlof, 1982), firms can raise workers' effort offering a wage "gift" above the required minimum.

The efficiency wage model in all its variants (Stiglitz, 1986; Katz, 1986) provides a rationale for the fact that job attributes not affecting directly workers' utility can indeed affect the structure of relative wages. Efficiency wage theories predict in fact that profit-maximising firms may find it profitable to raise wages above the market clearing level for the type of workers they want to attract. At least some employers may pay non-competitive wages in order to minimise turnover costs, if they bear part of the quit-associated costs and turnover is inversely related to the wage workers are paid. Wages above the going rate may be offered to try and increase workers' effort, by making a potential job loss more costly and so creating an incentive for workers to perform better. Higher than competitive wages may be paid in order to establish a "gift exchange" relationship between firms and workers, by which workers' productivity rises due to a feeling of loyalty to an employer who shares rents with his employees. Finally, some firms may use wages as a selection rather than an incentive device and offer higher wages in order to attract workers of a better, but unobservable, quality.

The key issue in explaining the observed structure of relative wages across firms is imperfect information. If employers are identical in the way they face and deal with imperfect information, then efficiency wage theories just imply that workers of the same quality may be paid wages above the market clearing level, but all firms will pay the same wage for the same type of workers. If, instead, employers differ in their ability to face turnover costs, to measure the productivity of workers, or to monitor them, either because of differences in management capacity, or because of differences in the technology of production, then this may be reflected in substantial wage differentials for similar workers. The optimal wage will be different among firms and if some forms of imperfect information - like those giving rise to turnover costs or monitoring costs - depend on industry specific characteristics, such as the technology of production, then firm-level differentials will be reflected, at the more aggregate industry level, in significant inter-industry wage differentials. The efficiency wage hypothesis can therefore account for the fact that job attributes that don not affect the utility of workers, like their affiliation to a certain industry of production, may indeed affect their wage rates (Krueger and Summers, 1988).
This indirect implication of efficiency wage theories in terms of the inter-industry structure of wages can be exploited to test the efficiency wage hypothesis in an empirical analysis. It is only an indirect approach, since a direct approach would entail an evaluation of the relationship between wages and workers' productivity/effort. But it has the advantage of being relatively easy to implement using data with information about individual workers' characteristics, income and industry affiliation, of the type currently available for several countries.

Another possible explanation of the inter-industry wage structure, in the class of non-competitive theories of the labour market, is the one arising from the insider-outsider model (Lindbeck and Snower, 1988c). The theory accounts for wage differences among industries which are stable across different occupational groups, age brackets and seniority levels within the same industry. In the insider-outsider theory the source of wage premia is the existence of relevant turnover costs. Turnover costs give rise to a certain degree of insiders' market power in setting the wage above the market clearing level, without taking the interest of outsiders into account. Different versions of the insider-outsider model focus on different forms of turnover costs: hiring, firing and training costs (Lindbeck and Snower, 1984, 1987b; Solow, 1985); costly time needed to negotiate the exchange of insiders for outsiders (Shaked and Sutton, 1984); reduced productivity of new entrants because of poor future perspectives in terms of job security and advancement and, consequently, little incentive to build good reputations (Lindbeck and Snower, 1988a); lower productivity of entrants when insiders refuse to cooperate with them or harass them (Lindbeck and Snower, 1988b). The existence of turnover costs gives the insiders a relative advantage over the outsiders, which they can exploit in the wage bargaining process with their employers. Firms and their insiders then share the economic rent from insider employment. The insiders' share of the economic rent will be larger, the higher the turnover costs (the larger the total size of the rent) and the more firms stand to lose from a breakdown in wage negotiations (the smaller the firms' share of the rent).

The insider-outsider model of wage determination (Lindbeck and Snower, 1990) assumes a fixed number of identical firms in each industry, producing a homogeneous product. Each firm in a given industry is an imperfect competitor in the product market and makes its price, production and employment decisions taking wages as exogenous. The firm maximises profits net of turnover costs, thus determining the optimal level of price,
production and employment. Wages are then set through a bargaining process between each firm and its insiders, taking the effect of the decisions on price, production and employment into account. The insiders can be assumed to bargain either individually or collectively through a union. If they bargain individually, both the firm and each insider take the behaviour of all other insiders as given. In other words, the firm is assumed to bargain with the marginal insider after having already reached wage agreements with all other insiders and retained them. If insiders bargain collectively, the union is assumed to comprise all of them and the union’s wage objectives are formulated in order to ensure that all insiders are retained, while ignoring the interests of outsiders. Therefore, in both cases, the objective of the bargaining process is the economic rent associated with the employment of the marginal insider. Also, all insiders are supposed identical in terms of productivity, bargaining strength and turnover costs.

Wage negotiations take the form of a Nash bargaining, where the utilities of the firm and the marginal insider, net of their outside opportunities, are jointly maximised. The negotiated equilibrium wage is the outcome of this maximisation process and is related - among other things - to the firm’s profit opportunities, its capital-labour ratio, the concentration ratio in the product market, and the degree of insiders’ bargaining power. In particular, the higher the profits, the capital-labour ratio, the concentration ratio and the insiders’ bargaining power, the higher the negotiated wage. These factors are the same for all firms in a given industry, because by assumption firms in the same industry are identical. But if these factors vary across industries - as it seems plausible -, the negotiated wages will also vary across industries and the model will imply the existence of relevant inter-industry wage differentials.

The propositions about the relationship between profits, capital-labour ratio and concentration ratio on one side and the wage rate on the other side are in principle testable. The hypothetical relationship between insiders’ bargaining power and wages, instead, is not directly testable, because insiders’ power is not directly measurable\(^3\). However, insiders’ bargaining power tends to be positively related to the degree of unionization and the extent of legal job protection (Lindbeck and Snower, 1990), which can be measured through a variety of indices. Note that in the insider-outsider model the presence or absence of unions

\(^3\) Insiders’ bargaining power is defined as the marginal increase in the wage rate due to a marginal increase in turnover costs.
does not affect directly the equilibrium wage, since wage bargaining takes place between a single firm and its insiders either individually or collectively with an identical outcome. But unions and job protection legislation can have an influence on wages indirectly, by affecting the insiders' bargaining power. In any case, as we will see in the next Section, the empirical implementation of a test for the various implications of the insider-outsider model meets with several difficulties in terms of availability of data and econometric technique.

2.4 Empirical Implications for the Inter-Industry Wage Structure

In this Section I will illustrate the statistical method employed in the next Chapters for the measurement of inter-industry wage differentials and their interpretation. The general empirical strategy for evaluating the alternative theories of wage determination presented in the previous Sections consists in the estimation of conveniently specified earnings functions using data at the individual level. The wage regressions to be estimated can be easily derived from the previous theoretical analyses. I will start from the simple earnings functions of human capital theory; then I will move on to consider the model generally used to test the theory of compensating differentials; finally, I will present the model suggested in the empirical literature to evaluate non-competitive theories of wage determination through the existence of significant inter-industry wage differentials. This approach reflects both the historical evolution of empirical analyses of earnings functions and a methodological development from a particular to a more general specification of the econometric model. A number of measurement problems will be considered at each stage. Some of the issues emerging with the simplest earnings functions, in fact, are related to the problems arising in subsequent, more complex specifications and in particular with the correct measurement of inter-industry wage differentials.

Human capital theory of wage determination is commonly assessed by estimating, with the least squares method, a standard earnings function of the form:

$$\ln w_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \beta_3 x_i^3 + u_i, \quad i = 1, \ldots, N, \tag{2.12}$$
where $w_i$ is a measure of the wage rate of individual $i$, $s_i$ and $x_i$ are years of schooling and of working experience of individual $i$ respectively, and $u_i$ is a stochastic error term assumed to be $u_i \sim IN(0, \sigma_u^2)$. The schooling coefficient $\hat{\beta}_1$ provides an estimate of the rate of return to education, assumed to be constant in this specification. The concavity of the observed age-earnings profile is captured by the quadratic form for the experience terms, whose coefficients $\hat{\beta}_2$ and $\hat{\beta}_3$ are expected to be positive and negative respectively. The schooling variable is usually expressed as years of full-time education. For the working experience variable, three possibilities are typically considered. The first was originally proposed by Mincer (1974) and consists in a transformation of the individual's age as a proxy for his experience: age minus schooling minus six (the age at which school begins). The second is to use directly the age of individuals as a proxy. Age tends to be very strongly correlated with experience in the samples considered in empirical studies of earnings, especially for male workers. The third is a direct measure of labour force experience through biographical schemes. This last possibility provides in principle the most accurate variable, but in practice is subject to serious measurement errors. The estimate of equation (2.12) with cross-sectional data, the most common practice in empirical literature on human capital, rests on the assumption that the economy and population are in long-run, steady state equilibrium, so that the earnings function holds across individuals in each period and also describes the longitudinal earnings path of representative individuals over the life cycle.

In order to take into account the various critiques of the strong, unrealistic assumptions underlying the simplest form of human capital theory, other variables have been subsequently added to equation (2.12). Variables like ability and family background, believed to have both a direct and an indirect effect on earnings, may lead to upward biased estimates of the rates of return to education and on-the-job training if omitted in a simple equation such as (2.12) and if such equation is estimated with the ordinary least squares method. The measurement of complex factors like family background and ability, given the limited nature of available data, has generated various problems (Atkinson, 1983).

Empirical studies on the relationship between ability and earnings have essentially concentrated on the inclusion of "measured IQ" scores as an explanatory variable. Unfortunately, this is not only a rather questionable measure of intelligence in itself, but also
- in the best of cases - a measure of only one dimension of ability (intellectual capacity). Evidence about IQ and earnings suggests that the independent influence of IQ is very small (Bowles and Gintis, 1973). The apparent association between intelligence and earnings may simply derive from the fact that they are both related with other variables like family background, education and training. A similar conclusion has been reached in other studies (Griliches and Mason, 1972; Taubman, 1975), even in the context of simultaneous equations with errors of measurement models. Griliches (1977) even shows that under quite realistic and not too restrictive conditions (a small measurement error in the education variable), the estimate of the rate of return to education can indeed be downward rather than upward biased as a consequence of the omission of ability variables. In general, the inclusion of ability measures has not had, form an empirical point of view, a significant impact on estimates of the rate of return to schooling, thus suggesting the conclusion that the "ability bias" is in fact small (Willis, 1986; Rosen, 1992). All these studies, however, share a certain number of methodological limitations. Samples of data are often of a rather peculiar nature (Second World War veterans of the U.S. armed forces, men who took the Aviation Cadet Qualification Examination, etc.). Moreover, variables such as IQ scores may be reported with considerable measurement errors.

Similar measurement problems arise when considering the family background variable. The indicators that are usually included in estimated earnings functions represent rather poor proxies, again due to the limited nature of available data. Fathers' education and occupation are some examples. These variables are also subject to serious measurement errors, since they usually refer to information provided by the respondents, rather than by other family members. Evidence about the relationship between these measures of family background and earnings is rather mixed (Bowles, 1972; Psacharopoulos, 1977). The admission of the essentially unobservable nature of family environment has led to studies which try to "control" for its effect on earnings by considering individuals from the same family. Studies on brothers and twins are also supposed to correct for other genetic components of ability and background. The procedure consists in relating the difference between the earnings of siblings with the difference in characteristics like education and working experience. Evidence about the importance of environmental and genetic factors is again mixed. Griliches (1979) found that the estimated return to education obtained in this way is very close to that obtained from equations which do not control for these factors, thus suggesting that their influence on
earnings is only minor. Taubman (1976) instead estimates that genetic endowment accounts for about 45% of the variability of earnings and family environment for about 12%. More advanced econometric techniques used in these studies highlight, at the same time, a number of methodological problems. Since data on siblings refer to a group of people more similar than the population in general, measurement errors may have more serious consequences (Griliches, 1979). Moreover, the specific samples of siblings used in these studies are rather questionable as being representative of the entire population or even of the population of siblings.

A further major problem with a simple least squares estimate of an equation like (2.12) is the endogeneity of education. As we have seen in Section 2.2, education is the result - at least in part - of optimizing behaviour by individuals. The optimal educational decision is based on expected future earnings and as far as expected and actual (ex-post observed) earnings are correlated, this behaviour may induce an additional correlation between the education variable and the error term in equation (2.12). This in turn implies biased estimates of the rate of return to education. A complete solution of the endogeneity problem would imply the specification of a model of individual optimal behaviour and its inclusion in a general equilibrium solution for the economy as a whole (Griliches, 1977). Work in human capital theory has focused on modelling individual optimal behaviour (Ben-Porath, 1967), but only to produce econometrically intractable results. Rosen (1973) proposes a simpler model based on a number of very strong assumptions, which has been estimated by Griliches (1977) using the method of instrumental variables. He finds that the simple least squares estimates of the education coefficient may actually be seriously under-estimated rather than over-estimated. Willis and Rosen (1979) formulate an econometric model, based on the model by Lee (1976) (found in Maddala, 1983), which involves a two-stage method: a reduced form probit for the probability of choosing a certain level of education in the first stage and an earnings function which corrects for selectivity bias in the second stage. The problem of identification of the model is far from trivial (Willis, 1986). Their empirical findings also indicate the possibility of a significant downward bias in the uncorrected least squares estimates of the rate of return to education. Given the non-representative character of the data set they use (the NBER-Th sample of men who had volunteered for pilot, bombardier and navigator programmes of the U.S. Army Air Force during WW II), it is rather difficult to reach firm conclusions about the magnitude or even the direction of the bias and to extend
any conclusions to non-U.S. data. Griliches (1977) concludes his analysis of the endogeneity of education by saying:

"Whether the [endogeneity] problem is really serious depends on one's view as to how close individuals are to guessing their own and the economy's future and to what extent their actions can be interpreted as optimizing. I would think that it is not as serious as it appears at first sight because of (i) the large influence of random, and probably unanticipated, events on the actual earnings experience of an individual and (ii) the large influence of parents, the state, teachers, and classmates on the actual level of schooling achieved by an individual, only part of which can be interpreted as the result of his own ex-ante optimizing behavior." (Griliches, 1977, p.13).

A similar view is shared by Willis (1986), who concludes:

"My impression is that the simple Mincer-type earnings function does a surprisingly good job of estimating the returns to education even though more general econometric models suggest that the conditions (...) upon which it is based are not strictly true." (Willis, 1986, p.590).

A radically different approach to the problem of ability and self-selection bias in estimating the returns to education (and post-schooling investment in on-the-job training) has also been suggested in recent studies, the "experimental" approach (see Burtless, 1995; Heckman and Smith, 1995 for comprehensive surveys). This approach has been adopted in the U.S. to evaluate the effectiveness of a variety of public policy programmes, including public sector-sponsored training programmes (LaLonde, 1995). In the experimental approach, differently from the "non-experimental" or "econometric" approach, the researcher has direct control over the variables under investigation. Individuals are randomly assigned to a recipient or "treatment" group and a non-recipient or "control" group and the differences in average responses between the two groups are then observed. Such a method has been used to estimate the returns to job training programmes while avoiding the potential bias induced by unobservable ability and endogeneity of the training decision. The evidence suggests that returns to training estimated in a traditional econometric model may indeed be considerably upward biased. This seems to suggest that a similar problem might arise in the least squares estimates of the returns to education in equations like (2.12), due to a basic methodological problem. However, the experimental approach has also been subject to a number of
methodological criticisms. Social experiments can be correctly employed only in very restrictive circumstances and often cannot provide an answer to the questions of interest. More relevant, although they solve the problem of the unobservable ability and endogeneity bias, their results are also affected by potential bias: a randomization bias may occur if the procedure of random assignment causes the type of individuals that participate in a programme to be different from the type of individuals that would participate in the programme in normal conditions; a substitution bias may occur if the members of the experimental control group have access to close substitutes for the experimental treatment (Heckman and Smith, 1995). These are circumstances that can hardly be avoided in the practical implementation of social experiments and that can distort considerably the evidence emerging from them.

Psacharopoulos and Layard (1979) emphasized two further inadequacies of a simple equation like (2.12). The first is the specification of the education variable in terms of years of full-time schooling. They suggested that earnings are better explained by educational qualifications (expressed by a set of binary dummy variables), especially if part-time education is a relevant form of investment in human capital. The second is the assumption of no interaction between education and post-school on-the-job training (parallel experience-earnings profiles). Accordingly, they included in their earnings equation various schoolingxexperience (both measured in years) interaction terms. Their empirical evidence for Great Britain found substantial support for both criticisms.

Simple earnings functions of the type illustrated by equation (2.12) have nevertheless provided remarkably stable estimates for the rate of return to schooling, for various time periods and different countries (see Willis, 1986 for a survey of empirical results). Even when enriched with other personal and environmental variables thought to influence earnings, the relative uniformity of findings over time and across countries is only marginally affected (Rosen, 1992). However, this kind of regressions typically explains only about 30% of the variation in wages (Willis, 1986, Table 10.5), living room for other complementary or competing theories of wage determination.

The theory of compensating wage differentials can be thought as such a complementary explanation with respect to human capital considerations. The earnings function usually estimated to test this theory consists in an equation like (2.12) additively augmented with controls for working conditions:
\[ \ln w_i = \beta_0 + \beta_1 s_i + \beta_2 x_i + \beta_3 x_i^2 + \gamma' y_i + \nu_i, \quad i = 1, \ldots, N. \] (2.13)

where \( y_i \) is a vector of \( j \) measures of working conditions for individual \( i \), scaled so that higher values of \( y_i \) indicate less desirable jobs, and \( \nu_i \) is a random disturbance satisfying the conventional assumptions. For individuals with given personal characteristics, the theory implies that \( \partial w_i / \partial y_i = \gamma_j > 0 \), for all \( j \).

Studies of the relationship between working conditions and earnings (surveyed by Brown, 1980) have included a large variety of indicators of working conditions as explanatory variables. These are typically specified as qualitative, discrete variables and often simply as binary 0/1 dummies, where the value 1 indicates the existence of some unpleasant condition. Examples are dummies for jobs that require performing repetitive functions, physical strength, working under stress, that involve a bad working environment (noise, smoke, extreme heat or cold, dirt, humidity, vibrations, hazardous materials and equipment), no flexibility of working time (punch clock, no freedom to take time off) or excessive overtime. Examples of indicators measured on a continuous scale are the proportions of deaths or lost workers due to working accidents. Since the classification of unpleasant working conditions implies a certain amount of subjective judgment, some authors have tried more direct measures like the perceived advantages of a certain job or the degree of satisfaction associated with it (both discrete variables measured on some arbitrary scale). All these indicators represent approximate measures of a multi-dimensional concept such as working conditions. Their inclusion in earnings functions, therefore, solves the problem of unobservable characteristics only to a limited extent.

Empirical research has provided only inconsistent support for the theory of compensating differentials, often with wrong-signed or insignificant estimates of the compensating premia. A major problem may arise if other measures of the personal characteristics of individuals (for example ability) are omitted from equation (2.13). If these characteristics are negatively correlated with unpleasant working conditions - as they are likely to be - the estimate of compensating premia is biased downwards (Brown, 1980). To overcome this difficulty, some authors (Brown, 1980; Duncan and Holmlund, 1983) have used
longitudinal data to "control" for unmeasurable workers' characteristics (I will return to this approach later). Even in this case, the plausibility of the estimates is not markedly improved. The theory of compensating wage differentials is therefore generally rejected as a candidate for explaining residual earnings variability across individuals with given human capital endowments.

The statistical approach to building an indirect test for the efficiency wage and the insider-outsider hypotheses starts again from a standard human capital earnings function, enriched with controls for working conditions and with a set of dummy variables for industry affiliation of individual workers:

\[
\ln w = X\beta + Y\gamma + D\delta + e,
\]

where \(X\) is a matrix that summarizes all human capital attributes, \(Y\) is a matrix of controls for working conditions, \(D\) is a matrix of industry dummies which captures inter-industry wage differentials, and \(e\) is a disturbance term with the usual statistical properties. Under the hypothesis of a competitive model of wage determination - if the list of controls is complete - the estimated coefficients of industry dummy variables would not be significantly different from zero. Alternatively, under the assumption of a non-competitive model - like in the efficiency wage or insider-outsider theories - inter-industry wage differentials are statistically significant even after controlling for varying human capital characteristics and working conditions. In the following Chapters I will present several pieces of statistical evidence concerning this issue, and therefore I defer to that context detailed comments on empirical results previously obtained.

A major problem affecting the estimation of inter-industry wage differentials by an earnings function like (2.14) is worth mentioning here (Thaler, 1989). Before significant inter-industry wage differentials can be regarded as genuine evidence in favour of non-competitive theories, a simple explanation in purely competitive terms must be ruled out. Higher industry wages might just reflect a better labour quality. In spite of the various attempts previously illustrated, ability and family background (and partly working conditions)
remain substantially unobservable factors. The unobservable labour quality explanation is difficult to evaluate. As we have previously seen in this Section, the unobservable labour quality bias can affect the estimated returns to education. The exact measurement of an unbiased coefficient for the rate of return to education is not the main concern in the context of inter-industry wage differentials. However, the unobservable ability bias in a simple least squares estimate of a model like (2.14) can affect both the coefficients of the education variables and the estimated inter-industry wage differentials. The precise, separate consequences of this general misspecification problem (omitted variables) on the two sets of coefficients are difficult to detect. A first method, suggested by Krueger and Summers (1988), consists in comparing inter-industry wage differentials estimated from equation (2.14) with and without the other control variables \((X\) and \(Y\)). If unobservable labour quality is positively correlated with observable quality and industry wage differences are due to differences in unobservable labour quality, then the inclusion of observable labour quality measures should substantially reduce the industry effects. Krueger and Summers have observed that the addition of a large number such controls (34) implies to a reduction of the standard deviation of industry wage differentials of only 1%. Moreover, industry differentials estimated with and without controls are highly correlated. These results have led them to conclude:

"Unless one believes that variation in unmeasured labour quality is vastly more important than variation in age, tenure, and schooling, this evidence makes it difficult to attribute inter-industry wage differences to differences in labour quality." (Krueger and Summers, 1988, p.269).

However, other authors have produced contrasting evidence in support of the unobservable labour quality explanation (Murphy and Topel, 1987).

A second approach to the unobservable labour quality problem is to consider evidence from panel data and estimate earnings functions with techniques which permits to control for fixed effects. Ability and other aspects of unobservable labour quality are in fact supposed to remain constant over time. This method implies to looking at workers who change jobs and switch between industries. This raises a complex issue of measurement errors, since workers who appear to have switched industries may have just been incorrectly recorded in the wrong industry at some stage. Moreover, there is a potentially serious problem of selectivity bias.
Workers who switch from low-wage industries to high-wage industries might just be workers with better labour quality. This selectivity bias induces an upward bias in the estimated inter-industry wage differentials because switchers might have unobservable quality differences positively correlated with industry wage differences. Evidence from longitudinal data seems inconclusive. Krueger and Summers (1988) still found substantial inter-industry wage differentials, similar in size and significance to those obtained from a cross-sectional approach. Murphy and Topel (1987) estimated much weaker industry effects and concluded again in favour of the unobservable labour quality explanation. These conflicting results are rather difficult to evaluate, since the various studies tend to use different data sources and different procedures.

Assuming that unobservable labour quality is not biasing estimated inter-industry wage differentials, substantial industry effects can be regarded as evidence consistent with non-competitive theories of wage determination. As we have seen in Section 2.3, both efficiency wage and insider-outsider theories predict the existence of significant industry wage differentials. But for the very same reason, a discrimination between the two theories is difficult. Inter-industry wage differentials are only a possible indirect consequence of efficiency wage considerations, not a necessary one. Nor are they a sufficient condition for efficiency wages to be a legitimate theory. If significant industry differentials are estimated from a regression model like (2.14), all we can say is that the evidence is consistent with the efficiency wage hypothesis. But this type of evidence is also consistent with the insider-outsider model.

Lindbeck and Snower (1990) suggest a different, more direct strategy to test the insider-outsider hypothesis and discriminate between this theory and both the competitive theory and the efficiency wage theory. With reference to the factors affecting equilibrium industry wages in the insider-outsider context illustrated in Section 2.3, the competitive theory of the labour market does not explain why the inter-industry wage structure should be related to inter-industry differences in concentration ratios and union density. And the efficiency wage theory cannot explain the relationship between wages and union density and profits across industries (Lindbeck and Snower, 1990). So if these factors appeared significant determinants of industry wages in an empirical analysis, the evidence would be consistent with the insider-outsider theory and rule out alternative explanations. In particular, if union density was a significant variable in explaining wage differences across industries, this would
allow to reject both competitive and efficiency wage theories and leave insider-outsider considerations as the only possible rationalization.

However, it is not very clear from Lindbeck and Snower's analysis which kind of econometric model and data would be appropriate for such a test. Any possible specification of an econometric model relating wages to insider-outsider factors and other wage determinants, such as human capital characteristics and working conditions, would entail variables which are typically defined at different levels of aggregation. The wage rate, human capital characteristics and working conditions are defined at an individual level. Profits and capital-labour ratios are firm specific aspects. Concentration ratios and union density can be properly measured at an industry level. The use of industry averages for the variables defined at a lower level of aggregation implies a considerable loss of information and does not seem very satisfactory. On the other hand, the inclusion of variables referring to different levels of aggregation in the same econometric model may generate inconsistent estimates (Dickens and Ross, 1984). Moreover, this kind of variables are usually not available from a unique data source and this may represent a serious limitation to the practical implementation of such an empirical test.

Efficiency wage and insider-outsider theories are regarded as general hypotheses about the process of wage determination and therefore, at least in the opinion of their advocates, their validity should hold over time as well as across different countries. If this is not the case, other aspects of the wage setting process must be considered, in order to account for possible variations in wage structures. This is essentially the empirical strategy I will adopt to verify the impact of institutional conditions in the labour market, and in particular of the degree of centralization, on the inter-industry structure of relative wages. Earnings functions like (2.14) will be estimated for different countries and the resulting inter-industry wage structures will be compared. Under the hypothesis of a general non-competitive theory of wage determination, inter-industry wage differentials should be substantial and similar across countries. If instead their size and significance change across countries, the various countries will be examined in terms of their peculiar labour market institutions and the relationship between the degree of centralization of wage bargaining and the structure of industry wages will be investigated. Unfortunately, longitudinal data for all the countries analyzed in the later Chapters of this thesis are not available. The possibility of unobservable characteristics bias
will be taken into proper account and its relevance evaluated using the first approach suggested by Krueger and Summers (1988).

2.5 The Degree of Centralization of Wage Bargaining

Following Tarantelli (1987), I define the degree of centralization in wage bargaining as one of the main dimensions of a labour market characteristic termed "corporatism" by political scientists, the others being the degree of cooperation between trade unions and employers' representatives in wage bargaining and the system of regulation of industrial conflicts. According to Bruno and Sachs (1985), corporatism is in turn one of the two important dimensions of labour market flexibility, together with nominal wage responsiveness to changing labour market conditions. It is therefore clear that the degree of centralization represents only one of the aspects of the broader concept of labour market flexibility, but hopefully one which is more easily measurable.

In their attempt to classify different countries according to the degree of centralization of wage bargaining, various authors have considered several definitions of centralization, each of them putting emphasis on different factors characterizing the process of wage setting. Bruno and Sachs (1985) focus on the level at which wage negotiations proceed and on the extent of coordination within trade unions and employer associations. According to them, the key feature is voting on collectively bargained agreements. A similar but more limited aspect is emphasized in the definition provided by Calmfors and Driffill (1988). They define it as the extent of inter-union and inter-employer cooperation in wage bargaining. The focus is therefore on the extent to which coalitions are formed among unions and employers respectively, that is on the behavioural content of wage setting rather than on the formal one, as it is the case when we consider the level at which bargaining occurs. Other authors - reported and discussed by Calmfors and Driffill (1988) - define centralization according to similar criteria. Schmitter (1981) considers only the union side. Cameron (1984) takes into account only the union side, but in addition he considers the extent of unionization, in an attempt to measure cooperation among workers in general rather than among unions only. Blyth (1979) relies on two criteria: the extent to which coalitions are formed within unions and within employers in actual wage bargaining and the level at which bargaining takes place. A much more comprehensive definition of centralization is proposed by Tarantelli (1987).
According to him, a centralized system of industrial relations is characterized by bargaining mainly taking place at the national and/or industrial or regional level, rather than at the company and plant level, by a high degree of coordination within the organizational structure of trade unions, by a few key contracts influencing directly or indirectly a high percentage of the labour force, and by bargaining taking place at close - for example, one year - and non-overlapping or synchronous intervals. This last condition is particularly interesting, since it attempts to measure the possibility of fine-tuning wage agreements preserving the structure of relative compensations in the presence of changing economic conditions. Finally, Freeman (1988) suggests the use of union density as a very simple indicator of the degree of centralization. The main problem with this approach is to judge the extent to which differing unionization rates actually reflect differences in the formal or informal coverage of union contracts (Calmfors and Driffill, 1988). Moreover, differences in national definition and measurement are likely to affect the comparability across countries. Freeman himself concludes from his empirical analysis that after controlling for other indicators of centralization, union density does not play a significant additional role in explaining inter-industry wage differences (Freeman, 1988).

Despite the general agreement about the significant role played by labour market institutions from a theoretical point of view, existing empirical analyses of the relationship between the degree of centralization and the associated wage dispersion, on one side, and global labour market performance, on the other side, have offered conflicting interpretations. Some studies (Bean, Layard and Nickell, 1986; Newell and Symons, 1987; Layard et al., 1991) relate good outcomes with respect to employment and unemployment to centralized labour markets with low wage dispersion, where large and all-encompassing trade unions take into account the unemployment effects of wage determination. Others (OECD, 1985 and 1987) associate labour market success with decentralization of wage setting and greater cross-industry wage dispersion, since a higher flexibility of relative wages allows greater scope for industry-specific factors. Finally, some authors (Calmfors and Driffill, 1988; Freeman, 1988) postulate the existence of a non-monotonic relationship between centralization/dispersion and the labour market performance, with countries having highly centralized institutions and low wage dispersion and countries with highly decentralized bargaining and high wage dispersion both showing better employment outcomes than countries with intermediate types of wage structure and labour market institutions. These
divergences in the conclusions about the relation between wage dispersion, institutions and economic performance show, among other things, the danger of generalizing from results based on aggregate data, the type of data used in the studies previously mentioned. On the one hand, countries exhibiting a similar degree of wage dispersion at an aggregate level are characterized by very different institutional frameworks and wage bargaining procedures. For example, the U.S. and Austria, which are generally regarded as extreme cases of decentralization and centralization respectively, are both classified by Freeman (1988) as having a high and increasing degree of wage dispersion within OECD countries over the period 1970-86; similarly for Switzerland and Germany, as less extreme examples. On the other hand, countries forming natural pairs in institutional terms - such as Sweden and Norway, the U.K. and Ireland - present, again according to Freeman (1988), rather different degrees of dispersion in the inter-industry wage structure. The same sort of ambiguity can be detected within some of the above mentioned studies with respect to the relationship between indicators of the labour market structure and labour market performance, since countries with similar institutions may perform very differently - for example, the U.S. and Japan, Sweden and Denmark (Calmfors and Driffield, 1988; Freeman, 1988).

If cross-industry wage dispersion is used as the most important indicator of the underlying labour market institutions to be related to employment performances, average industry wages at an aggregate level are not a proper measure for evaluating the inter-industry structure of relative compensations. In fact, they may reflect many factors other than institutional characteristics which present wide variations across industries - like differences in technology and productivity - and which are perfectly consistent with the competitive theories of the labour market. In the empirical analyses of the following Chapters I will therefore try to measure inter-industry wage dispersion on a different basis: estimating earnings functions augmented with dummy variables for industry affiliation at an individual level, using micro-data.

2.6 Institutional Conditions for Wage Bargaining in the Countries Considered

In the light of the various definitions of centralization provided in the previous Section, I will now examine the principal institutional conditions for wage setting in the seven countries considered in later Chapters of this thesis - the United States, Canada, Australia,
Germany, the Netherlands, Austria and Sweden - in order to try to classify their degree of centralization of wage bargaining. Germany will be the main case studied in Chapter 4. Inter-industry wage differentials estimated with micro data for Germany will then be compared, in the same Chapter, with similar evidence from other studies for the United States, Australia, Austria and Sweden. The United States, Canada, Australia, Germany and the Netherlands will be analyzed in Chapter 5, looking at inter-industry wage differentials directly estimated from micro data for all countries. I will especially consider the institutional situation of these countries as it appeared in the mid-1980s, which is the relevant time period for my later empirical analyses.

2.6.1 The United States

The U.S. labour market is usually classified as one of the most decentralized among Western economies. Union density in 1984/5 was only 18 percent of non-agricultural wage and salaried employees and fell sharply during both 1970-79 (-6%) and 1979-85 (-7%) (Freeman, 1988). Wage negotiations occur predominantly at the enterprise and plant level. There is no traditional involvement by central organizations in bargaining: the main U.S. labour confederation, the AFL-CIO, does not bargain for its affiliated unions and therefore has never signed a wage contract; no national employer federation is engaged in the collective bargaining process. As a general practice, a large proportion of collectively bargained agreements must be ratified by individual union members. The U.S. system exhibits a largely unstable and complex network of pattern bargaining, with 195,000 collective agreements affecting about 25% of the labour force (at the end of the 1970s). Synchronization of contract renewals is very low and contracts have a long duration - often three years (Bruno and Sachs, 1985; Tarantelli, 1987; Calmfors and Driffill, 1988).

2.6.2 Canada

The Canadian labour market presents a very low degree of centralization, similar to that characterizing the U.S. economy. Union density in the mid-1980s was 28% among non-agricultural workers (Layard et al., 1991) and remained substantially stable both in previous and in subsequent years. About 50% of the work-force is covered by collective
agreements, which however concern a wide variety of industries and occupations and in the majority of cases are re-negotiated at the firm level. The Canadian Labour Congress is the recognized national union confederation, but it does not include many trade unions among the organizations it represents, so that the degree of coordination is in fact very low. The system of industrial relations is decentralized at the province level and is divided in 10 provincial systems and a federal system. Only the province of Quebec exhibits certain affinities with the European system, especially as far as the level of consensus between bargaining parties is concerned (Gunderson and Meltz, 1987; Streeck, 1992).

2.6.3 Australia

Union density in Australia in 1986 was 48% and has declined steadily over the period 1976-88 (Mitchell and Scherer, 1993). The main characteristic of the Australian labour market is the role played by industrial tribunals (about 100 courts for 6 millions of workers), invested with compulsory power of conciliation and arbitration. The activities of most employers, in most sectors of the economy, are subject to the legal determination of employment conditions set by these tribunals. Their decisions apply at different levels, both to particular employers and their employees and to national unions and employers' associations. The Australian Industrial Relations Commission (AIRC) assumes such a strong leading function in the decisions about national wage policies that the Federal Government cannot directly legislate, but has to ask for its cooperation. However, at the lower state level, local governments can legislate directly both about salaries and about working conditions. The industrial division of the Federal Court is responsible for the distribution of power between state system and federal system and also for the power of the AIRC with respect to other courts. In 1983, decisions taken in favour of the Federal Government at the expenses of the state influence have caused a shift of the bargaining system towards centralization.

The wage bargaining system operates at three levels. The AIRC sets general principles for pay increase. Industry-level bargains either follow these principles or have to be endorsed by the AIRC. All such bargains relate only to minimum wages. Firm-level bargains can agree "over-award" pay increases. Unions and employers often try to legally register new

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4 "Award" is a general legal term for a tribunal decision. In this context the term refers to decisions taken by the AIRC at the highest level of the bargaining system.
agreements stipulated at the firm-level. The tribunal can rejected these agreements, if they are regarded as too generous or too restrictive. Tribunal verdicts cannot be applied to similar cases affecting workers not directly involved in the dispute. The structure of Australian unions is extremely fragmented. Unions tend to be craft-based and are often very small. Employers can find themselves bargaining their employees’ wages and conditions with up to 20 different unions. Major innovations in the system of industrial relations were introduced in 1983 with the “Accord” between the Australian Labor Party (ALP) and the Australian Council of Trade Unions (ACTU). This agreement created, among other things, a commitment of the parties to wage moderation, an aggregation of unions into larger, industry-based organizations, and a more centralized system of wage negotiations. The Accord was signed in 1983, but started to be effective in terms of wage policies only in the period 1985-86. Its implementation was completed in 1990 (Cook, 1991; Layard et al., 1991; Archer, 1992; Mitchell and Scherer, 1993).

2.6.4 Germany

Germany presented in 1984/5 a moderate degree of union density, 42 percent of industrial employees, which exhibited an increase in the period 1970-79 (+5%) and remained constant in the period 1979-85 (Freeman, 1988). Collective wage agreements are normally struck within industries on a regional basis, but regional negotiations are closely coordinated by national trade unions and employer associations. Wage bargaining in the metal industry provides the guide-lines for negotiations in all the other industrial and service sectors. Trade unions and employer associations have comparatively centralized and encompassing organizational structures. There exists one central union confederation, the DGB, and single unions are organized on a branch basis - 17 branch trade unions associated with the DGB. A large proportion of employers are organized in associations, the most important of which - on a national basis - is the BDA. Central associations, however, are not usually involved in actual collective bargaining. Contracts signed in the metal sector by the metal industry union, the IGM, represent a benchmark for all the other contracts, thus influencing as a matter of fact a high percentage of the labour force. The duration of contracts is typically one year and negotiations take place throughout the year, though again the metal sector is considered to be
the key industry for setting the contract renewals pattern, which guarantees a fair degree of synchronization (Flanagan et al., 1983; Bruno and Sachs, 1985; Calmfors and Drifflf, 1988).

A distinctive feature of German collective bargaining is that the relationship between the trade unions and the employer associations is characterized by a relatively high level of cooperation and willingness to compromise. During the 1980s, trade unions accepted wage agreements which led - for the first time in the post-war era - to a considerable reduction of net real wages. In the spring of 1984, after the biggest strike in the history of West Germany, employers agreed to a reduction of the working week from forty to thirty-eight and a half hours and unions - with IGM as the pacemaker - consented in return to an increase in the degree of flexibility of working time. These agreements also reflect a general tendency toward the decentralization of industrial relations, implying a shift of competence in collective bargaining from an industry to a company level and a delegation of decision power to the management and work councils under the system of "co-determination", which is the peculiar institution of German industrial relations (Streeck, 1987; Jacobi and Mueller-Jentsch, 1990).

2.6.5 The Netherlands

In 1985 the Dutch union density was 29% and has constantly been decreasing over the period 1947-87 (Korver, 1993). In spite of the rather low percentage of union membership, the dominant aspects of the Dutch system of industrial relations are a high degree of centralization and an institutionalized cooperation among government, employers, and workers. Both trade unions and employers' associations are divided by industrial sectors and according to their religious/ideological connotation: there are 3 central unions - the NVV (social-democratic), the NKV (Catholic), and the CNV (Protestant) - and 2 major employers federations - the VNO (non-confessional) and the NCW (Christian). Collective bargaining takes place at the industry level: a few large organizations choose the contractual pattern and all industries tend conform to the agreements reached for the metal and construction workers. Wages are renegotiated every year. Participation of trade unions in government policies is very high. In 1982, unions and employers has reached an agreement about work-sharing practices. However, the decisions taken by the government in October 1983 - a wage decrease for public employees and a reduction in social security benefits - caused major strikes which endangered the renewal of this agreement in 1984 (Layard et al., 1991; Korver, 1993).
Austria has been considered as a paradigm of corporatism in all its various classifications. Union density in 1985 was 59% and has been slightly decreasing over the period 1950-1990 (Karlhofer and Ladurner, 1993). The structure of the Austrian "social partnership" (Sozialpartnerschaft) has two dimensions. Non-autonomous social partnership covers statutory corporations with compulsory membership such as the Chambers of Labour and the Chambers of Commerce, both with extensive rights of co-determination in questions of social security, employment and labour jurisdiction. Autonomous social partnership refers to the voluntary cooperation between employers' federations and labour organizations. The ÖGB is one of the strongest unions in Western countries. It is the actual protagonist of the specific Austrian form of corporatism and has a leading role in the autonomous social partnership. The ÖGB has almost absolute monopoly power, a high degree of concentration, with only 14 affiliates, and a high degree of internal coordination. Austrian employers are organized in the Chambers of Commerce. This association covers 100% of employers by compulsory membership and, therefore, is the primary partner of trade unions in collective bargaining. Representing extremely heterogeneous interests of members. The Chambers are often faced with problems of internal conciliation. The most important organization based on voluntary membership is the Federation of Austrian Industrialists, with 2,400 members employing 85% of the industrial labour force in the private sector. In principle, wage negotiations take place at the industry level. They are further distinguished in federal-, province- and company-level negotiations. In practice, however, federal-level agreements are binding for lower-level negotiations, which simply adjust for regional differences. Two ÖGB affiliates establish the bargaining pattern for all the other industries: the union of metal workers and the union of public employees. Collective agreements arranged by the ÖGB cover all wage and salary earners, whether they are or not members of the ÖGB. Most collective agreements, in particular wage agreements, are negotiated every year. Austria's corporatist success lies in the fact that social partnership constitutes an effective power both in industrial relations and in the political arena. Trade association have a decisive influence on all government bills before these are put to vote in Parliament (Guger, 1992; Karlhofer and Ladurner, 1993).
2.6.7 Sweden

The Swedish system is built around nearly universal union participation and this puts Sweden among the countries with the largest extent of union coverage. In 1984/5, 95 percent of blue-collar workers were represented in the national trade union confederation, the LO, and approximately 75 percent of white-collar workers were represented in two other union organizations, TCO and SACO-SR. The overall union density experienced a sharp rise both during 1970-79 (+10%) and during 1979-85 (+6%) (Bruno and Sachs, 1985; Freeman, 1988). The level of negotiation is highly centralized: detailed wage bargaining typically takes place at the industry level and then is further refined at the local level, but national level agreements serve as an essential guide-post for negotiations at the industry and firm level. The union confederation LO is organized along branch lines - 24 branch federations associated with the central organization. Employers are almost universally represented in the national employer confederation, the SAF. Central collective agreements are negotiated, without exception, between LO and SAF. Negotiators at the branch level have the power to reach agreements which are binding for all the members of the branch and individual union members voting on these agreements is virtually nonexistent. As a result, national and a few branch-level agreements affect almost the entire economy's wage setting. Synchronization of contract renewals is high and contracts duration is normally one-two years (Bruno and Sachs, 1985; Calmfors and Driffill, 1988).

Wage bargaining in Sweden has been crucially influenced by the "solidaristic wage policy". Initially conceived in 1936 and fully elaborated by LO in the 1950s with both growth and equity objectives, it developed along with government labour market programmes about training and labour mobility. The basic principle was "equal pay for equal workers": workers performing the same job should receive the same wage, irrespective of inter-industry differences in productivity and profitability. The principle has been implemented by raising the relative wages of workers in low-productivity sectors and by not fully exercising bargaining power in sectors with the greatest ability to pay. Lacking exact criteria for comparing jobs in different industries, the solidaristic policy has given way, since the 1960s, to a strictly egalitarian narrowing of wage differences between workers in different occupations (Flanagan, 1987). Wage increases at the local level in excess of the central agreements, the so-called "wage drift", became more important with real wage moderation.
after 1983. In 1984, the wage drift accounted for 40% of the hourly earning increases of blue-collar workers and for 61% of the hourly earning increases of white-collar workers in private industry (61% in 1984) (Flanagan, 1987).

From these various institutional conditions characterizing the process of wage setting, I believe we may conclude that the U.S. and Canada have an extremely decentralized system of wage bargaining, Australia, Germany and the Netherlands - in increasing order by degree of centralization - represent intermediate cases, Austria and Sweden have among the highest degrees of centralization of wage bargaining in Western countries. This view about the ranking of these countries is shared with several authors (Blyth, 1979; Schmitter, 1981; Cameron, 1984; Calmfors and Drifill, 1988; Freeman, 1988).

2.7 Conclusions

The explanation of industry wage differentials in terms of degree of centralization in wage setting procedures - and in general of labour market institutions - may be seen as a more general approach when compared with the efficiency wage and insider-outsider models. I believe that it is not in contrast with these two theories and that, in a sense, it encompasses both of them. Efficiency wage and insider-outsider theories are not independent of the institutional framework and can be considered as alternative microfoundations for wage determination, which become relevant under different labour market institutions. According to the efficiency wage models, firms are assumed to make both wage and employment decisions unilaterally. This assumption seems more realistic in a labour market characterized by a high degree of decentralization of wage bargaining, where workers have a limited market power in wage negotiations. In the insider-outsider model, the market power of the insiders in the bargaining process is certainly increased by a strong degree of unionization. This condition seems consistent with a high degree of centralization in wage setting. If we test the nature of the relationship between the degree of centralization of wage bargaining and the degree of wage dispersion, we may therefore get some insight of the potential relevance of efficiency wage and insider-outsider models in explaining the observed pattern of industry wage differentials.
In the following Chapters I will try to measure inter-industry wage differentials for different countries, using micro-data, and compare the resulting wage structures, in order to verify the possible existence of a relationship between wage dispersion across industries and the degree of centralization of wage bargaining.
References


Chapter 3

Analyses of the Inter-Industry Wage Structure with Aggregate Industry Wage Data

3.1 Introduction

Before proceeding to the analysis of inter-industry wage differentials estimated from micro data - which will be the topic of the next Chapters - I will consider in this Chapter some preliminary empirical evidence based on aggregate average industry wage data, as it emerges from studies provided by various authors. One of the findings which is often put forward as supportive of non-competitive explanations for industry wage differences is, in fact, the stability over time and across countries of wage structures measured by means of this type of aggregate data (Krueger and Summers, 1987; Katz and Summers, 1989).

I will show and discuss some of the results presented in two recent articles on aggregate industry wage differentials, the first by Krueger and Summers (1987) and the second by Gittleman and Wolff (1993). The authors, for their comparisons of industry wage structures over time and across countries, rely essentially on three different but complementary measures of association: the Pearson product-moment correlation coefficient, the Spearman rank correlation coefficient, and the coefficient of concordance.

The Pearson correlation coefficient is probably the best-known and most widely used measure of linear association between two random variables. However, the statistical properties of its sampling distribution are not totally obvious and only occasionally taken into account in economic applications. A clear understanding of these properties is especially important in the treatment of small samples, which is the situation faced by Krueger and Summers (1987) and by Gittleman and Wolff (1993) in most cases, as well as a recurring
characteristic of the analyses presented in the following Chapters of this thesis. The basic intuition of the nature of the problem is that even a sample Pearson correlation as large as 0.80 can be insignificantly different from zero, in rigorous statistical terms, if it is obtained from a very small sample.

The Spearman correlation coefficient is one of the oldest rank statistics and the oldest still in common use (Kotz and Johnson, 1988). Its purpose is to characterize an aspect of the relationship between two variables which is more general with respect to the Pearson correlation. While the Pearson correlation refers specifically to a measure of linear relationship, the two-rank Spearman correlation is generally a measure of monotone association. Its distribution properties are very rarely considered in practical applications. Again, this can lead to a serious misinterpretation of results in terms of statistical significance, especially when dealing with small samples of observations.

The coefficient of concordance is also a rank statistic, which measures the degree of agreement among more than two variables. In spite of being based on rank-orders, it is quite a different function with respect to the Spearman correlation. In particular, it varies between 0 (no agreement) and 1 (perfect agreement), rather than between -1 and +1. This statistic is almost universally - and possibly unjustly - neglected in economic applications. Only Gittleman and Wolff (1993) use this kind of multivariate (rather than bivariate) measure of association in comparisons of inter-industry wage structures. Although this multi-dimensional aspect makes the coefficient of concordance certainly attractive\(^5\), the fact that it is so rarely employed could be explained by the difficulty of comparing its values with those of other commonly used measures of association, like the Pearson and Spearman correlations (defined over the range \([-1, 1]\)). As an indicator of the "community of preference" or "agreement of vote" among individuals, it is sometimes employed in quantitative analyses by political scientists and sociologists (Kotz and Johnson, 1982).

In this Chapter, the three metrics will be carefully evaluated in terms of their statistical properties. These properties will then be applied to assess the statistical significance of the findings presented by Krueger and Summers (1987) and by Gittleman and Wolff (1993) for inter-industry wage differentials. Krueger and Summers (1987) do not conduct any hypothesis testing of the significance of their Pearson correlations, the only measure of association they

\(^5\) An alternative way to establish multivariate cross-country comparisons of inter-industry wage structures, based on a different methodology (minimum distance estimation), will be illustrated in Chapter 5.
consider. Gittleman and Wolff (1993) briefly mention the statistical significance of their Pearson correlations, but only for one of the several sets of results they present. Even in this case, they do not specify the null and alternative hypotheses actually tested, nor the significance level of their tests. Some more details are provided for tests of the statistical significance of their coefficients of concordance, but again only for one of the several sets of results. No hypothesis testing is conducted for the statistical significance of Spearman correlations. I will therefore try a complete and thorough evaluation of all the results presented in the two quoted articles, clearly specifying the methodology used in each case, stating explicitly the suitable null and alternative hypotheses, and setting appropriate significance levels for the various tests.

Both the studies considered here reach the conclusion that inter-industry wage structures are characterized by a high degree of stability over time and are highly similar across countries. Such a regular pattern seems to be explicable only by introducing non-competitive considerations and seems to deny any role of institutional or other country and time specific factors influencing the process of wage determination. This result will be challenged from two points of view. The first is the reliability and the actual statistical significance of the values obtained for the various measures of association used to judge the degree of stability of industry wage differentials. The second, and more relevant, is the overall appropriateness of aggregate wage data - as compared with micro data - as a basis for inter-temporal and cross-country comparisons of industry wage structures.

The rest of this Chapter is organized as follows. Section 3.2 illustrates the distribution properties of the product-moment correlation, of the rank correlation, and of the coefficient of concordance and explains how to build rigorous tests of their statistical significance.

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6 When discussing the Pearson correlations that appear in Panel A of their Table 2, Gittleman and Wolff declare, "While the correlation coefficients with the 1985 wage differentials generally fall the further back in time, they remain high (and statistically significant) in all cases." (Gittleman and Wolff, 1993, p.300). No further mention of the statistical significance of their Pearson correlations is made later in the article.

7 Presumably, that of no association/zero correlation in the population, against the alternative of some form of association/non-zero correlation, i.e. a two-tail test.

8 When discussing the coefficients of concordance that appear in Panel A of their Table 2, Gittleman and Wolff declare, "Calculating a chi-square statistic for the values of W shown in Table 1 [Table 2? Table 1 does not contain any value of W!] leads one to reject, at conventional significance levels, the hypothesis that the wage rankings across years are not associated." (Gittleman and Wolff, 1993, p.300, footnote 6). Again, no further mention of the statistical significance of their coefficients of concordance is made later in the article.
Section 3.3 presents and discusses empirical evidence provided by Krueger and Summers (1987) and by Gittleman and Wolff (1993) about the stability of industry wage structures over time in a variety of countries. Section 3.4 shows and evaluates the empirical findings of the same authors for cross-country comparisons of inter-industry wage differentials obtained from aggregate wage data. Section 3.5 examines the general conceptual limitations encountered by studies of the wage structure based on aggregate industry data, in comparison with analyses which use, instead, data at the individual level. Section 3.6 concludes with some final remarks.

3.2 Testing for the Statistical Significance of Product-Moment Correlations, Rank Correlations and Coefficients of Concordance

The two studies considered in this Chapter compare inter-industry wage differentials over time and across countries through the following measures of association: the Pearson product-moment correlation coefficient, the Spearman rank correlation coefficient, and the coefficient of concordance.

The purpose of these three alternative metrics is to characterize different aspects of the relationship between variates in a multivariate population. The Pearson correlation coefficient refers specifically to a measure of the linear relationship existing between two random variables. It is the most sensitive to the data in the samples actually used and provides, in the present context, an index of similarity between industry wage structures in a strong sense, because it relies on the exact size of wage differentials. It is also highly sensitive to outliers. The Spearman correlation coefficient is instead more general, being a measure of any monotone relationship between two variates. Since it considers rank-orders of values, this is easily seen from the fact that ranks are unaffected by any monotone, strictly increasing/decreasing transformation of the ranked variables. Also, it is not affected by extreme values or outliers. In the present context, it represents an index of similarity between industry wage structures in a weaker sense, because it relies only on the ranking of wage differentials across industries. In other words, it measures if the ordering of high- and low-wage industries tends to be stable between any pair of years or countries. The coefficient of concordance also relies on rank-orders of values, but, differently from the Spearman correlation, it represents a measure of the degree of agreement among more than two ranked
It therefore provides an overall index of similarity among industry wage structures in a weak sense, but over several time units or across more than two countries simultaneously. It is thus clear that each statistic measures a different, specific form of dependency or association between random variables and, therefore, direct comparisons among the three metrics can be misleading. Although the Pearson and the Spearman correlations are both defined over the range \([-1, 1]\), have the value zero when the two variables are independent, and values +1 (-1) for perfect positive (negative) linear association, they are otherwise quite different functions and comparisons between the two estimates are not particularly relevant (Kotz and Johnson, 1988). This is even more true for the coefficient of concordance, which is defined over the different range \([0, 1]\). Therefore, comparisons between estimates of the coefficient of concordance and estimates of the two correlation coefficients should be avoided.

The three metrics can be used to construct tests of the degree of association among variates, in my case of the degree of similarity among inter-industry wage differentials in various years or in different countries. The statistical significance of these statistics is highly sensitive to the sample size and care needs to be employed when interpreting evidence from very small samples, as it is the case for some of the results illustrated in the following Sections.

The distributions of the three metrics are characterized by being defined over closed intervals with finite bounds; the distributions of the Pearson and of the Spearman correlations are both truncated at -1 and +1, for the cases where there is perfect negative and positive association respectively; the coefficient of concordance ranges between 0 and 1, where 0 represents complete absence of agreement and 1 represents perfect agreement. As it will be illustrated in detail later, this particular form of the distributions implies a certain degree of arbitrariness in testing hypotheses for extreme positive values of the measures of association in the population. This limitation must be taken into proper account in the present context, since the relevant claims to be tested are in fact those of "very strong" stability over time and across countries of industry wage structures and, therefore, it is interesting to verify whether the values obtained for the three measures of association are significantly different from values sufficiently close to 1.

Moreover, with the exception of the Pearson correlation coefficient, the limited knowledge about the distribution properties of these statistics under alternative hypotheses permits in practice only a test of the null hypothesis of complete lack of association. This is
particularly unfortunate because it is not an especially interesting null hypothesis to be tested in the present context. Again, the relevant claim is that stability over time and across countries is "strong enough" to justify the conclusions drawn by Krueger and Summers (1987) and by Gittleman and Wolff (1993) about the nature of inter-industry wage differentials. Obviously, the authors are not claiming that "any" degree of positive association would be considered as supportive evidence. A value of a measure of association as small as 0.20 may well be significantly greater than zero, but can hardly be regarded as indicative of "strong" stability.

Let us now examine the appropriate testing procedures for each of the coefficients.

3.2.1 The Pearson Product-Moment Correlation

Consider a random sample of size \( n \) drawn from a bivariate normal population. The sample Pearson correlation coefficient between the random variables \( X \) and \( Y \), calculated from the set of \( n \) pairs of observed values \((X_i, Y_i)\), is defined as:

\[
r = \frac{n^{-1} \sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\left(n^{-1} \sum_{i=1}^{n} (X_i - \bar{X})^2\right)\left(n^{-1} \sum_{i=1}^{n} (Y_i - \bar{Y})^2\right)}}.
\]

The sample Pearson correlation \( r \) is an estimate of the underlying population Pearson correlation coefficient:

\[
\rho = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X) \text{Var}(Y)}},
\]
where $\text{Cov}(X,Y)$ is the covariance of $X$ and $Y$ and $\text{Var}(X)$ and $\text{Var}(Y)$ are the variances of $X$ and $Y$ respectively (Kotz and Johnson, 1982).

A variety of approaches have been suggested in the literature to approximate the properties of the sample Pearson correlation $r$, since it has not a well-behaved sampling distribution (see, for example, Kendall and Stuart, 1977). The exact distribution of $r$ was first derived by Fisher (1915). A first way to address the issue of its statistical significance is to construct two-sided confidence intervals for the population value $\rho$ using the sample correlation $r$ and an estimator of its standard error. Hotelling (1953) proposed the following expressions for the mean and standard deviation of $r$:

\[
E(r) = \rho \left\{ 1 - \frac{1 - \rho^2}{2(n - 1)} + \frac{1}{8(n - 1)^2} \left( 1 - 10 \rho^2 + 9 \rho^4 \right) \right\} + \mathcal{O}(n^{-3}), \tag{3.3}
\]

\[
\sigma_r = \frac{1 - \rho^2}{\sqrt{n - 1}} \left\{ 1 + \frac{11 \rho^2}{4(n - 1)} - \frac{192 \rho^2 + 479 \rho^4}{32(n - 1)^2} \right\} + \mathcal{O}(n^{-4}), \tag{3.4}
\]

where $\mathcal{O}(n^{-3})$ and $\mathcal{O}(n^{-4})$ stand for functions of higher order in $n^{-3}$ and $n^{-4}$ respectively (the remaining terms in the expansions).

For any $\rho$, as $n \to \infty$, the distribution of $r$ tends to normality as an immediate consequence of the central limit theorem and of Slutsky's theorem (Hotelling, 1953, p.212-213). In order to construct confidence intervals for $\rho$ I need a sample estimate of $\sigma_r$. This can be obtained by replacing the population $\rho$ in Hotelling's equation (3.4) with its sample estimator $r$. 

67
The terms of order $n^{-4}$ and lower order become negligibly small even for a very small sample size and can, therefore, be ignored. Since $r$ is a consistent estimator of $\rho$, by convergence in mean squared error (Hotelling, 1953, p.212), it follows that $s_r$ is also a consistent estimator of $\sigma_r$. Given asymptotic normality of $r$, I can thus construct confidence intervals for the population Pearson correlation coefficient. For example, a two-sided 99% confidence interval has the form:

$$r - 2.58s_r < \rho < r + 2.58s_r.$$

The estimated standard error $s_r$ in equation (3.5) is a monotone decreasing function of the absolute value of the sample correlation coefficient $r$. Therefore, the width of confidence intervals for $\rho$ tends to zero as the sample Pearson correlation $r$ approaches $1$ (-1). This implies that the estimate of the true population correlation $\rho$ becomes more accurate, the higher (lower) the value of $r$ observed in a sample.

In finite samples, however, the assumption of normality of the distribution of $r$ may be severely misleading (Fisher, 1915). As previously mentioned, the issue is particularly relevant for the applications contained in the following Sections. Krueger and Summers (1987) and Gittleman and Wolff (1993) calculate Pearson correlations for samples of rather small size, ranging from $n = 8$ to $n = 26$ for the various sets of industry wage differentials. The level of aggregation of the industry classifications chosen by the authors is always quite high and the size of their samples just reflects the small number of industry sectors considered.
FIGURE 3.1

Frequency curves for the correlation coefficient \( r \) of samples with \( n = 10, 50 \)

Source: Kotz and Johnson, 1983.

For small samples and high values of \( \rho \), the distribution of \( r \) is very asymmetric and
its variance is heavily dependent on \( \rho \). The skewness and the excess of kurtosis of the
distribution of \( r \) in small samples can be seen in Figure 3.1. This prevents a straightforward
use of \( r \) for drawing conclusions regarding \( \rho \) (Kotz and Johnson, 1983). As one can see
from equation (3.3) and Figure 3.1, \( r \) tends to underestimate \( \rho \), because the use of \( r \)
"cramps high values [of \( \rho \)] into a small space [near 1], producing a frequency curve trailing
in the negative direction and so tending to reduce its mean" (Fisher, 1915). The same holds,
symmetrically, for low values of \( \rho \) near -1. From equation (3.4) we also notice how the
variance of \( r \) is heavily dependent on \( \rho \). The derivation of \( s_r \) according to equation (3.5),
though asymptotically valid, may entail a considerable amount of bias in finite samples.

The consequences of non-normality of \( r \) and of bias in its standard error \( s_r \), can be
clearly seen in testing the extreme hypothesis of perfect positive linear dependence. When
\( \rho = 1 \), I have - from equations (3.3) and (3.4) - \( E(r) = 1 \) and \( \sigma_r = 0 \) for any \( n \), which
means that the frequency curve for \( r \) collapses into a spike at \( r = 1 \). Any observed value
of the sample correlation \( r \) smaller than 1, therefore, should lead to the rejection of the null
hypothesis $p = 1$. Setting the algebra aside, this is a pretty intuitive result. If $p = 1$, it means that the two variables under consideration are perfectly identical or one a simple linear transformation of the other in the population. In any sample drawn from such a population, the pairs of observed values of the two variables will also be identical or one the same linear transformation of the other as in the population and therefore the value of $r$ will always be equal to 1, whatever the sample size. In other words, the probability of observing $r < 1$ in a sample, when $p = 1$ in the population, is equal to zero. However, due to non-normality of $r$ and bias in $s_r$, if I try to construct an interval estimate for $p$ based on $r$ and on equation (3.5) for its standard error, results can be rather different. For various sample sizes and different values of $r$, I obtain the following two-sided 99% confidence intervals:

<table>
<thead>
<tr>
<th>$n$</th>
<th>$r$</th>
<th>$s_r$</th>
<th>99% Confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0.16</td>
<td>0.327</td>
<td>-0.683 - 1.003</td>
</tr>
<tr>
<td>20</td>
<td>0.16</td>
<td>0.224</td>
<td>-0.419 - 0.739</td>
</tr>
<tr>
<td>10</td>
<td>0.60</td>
<td>0.236</td>
<td>-0.009 - 1.209</td>
</tr>
<tr>
<td>20</td>
<td>0.60</td>
<td>0.154</td>
<td>0.202 - 0.998</td>
</tr>
<tr>
<td>10</td>
<td>0.99</td>
<td>0.009</td>
<td>0.966 - 1.014</td>
</tr>
<tr>
<td>20</td>
<td>0.99</td>
<td>0.005</td>
<td>0.976 - 1.004</td>
</tr>
<tr>
<td>36</td>
<td>0.99</td>
<td>0.004</td>
<td>0.981 - 0.999</td>
</tr>
</tbody>
</table>

With a sample of only 10 observations, even a sample correlation as small as $r = 0.16$ fails to reject the null hypothesis $p = 1$. All the more so, a correlation $r = 0.60$ will also fail to reject the null hypothesis $p = 1$. But at the same time, when $n = 10$, both values of the sample correlation fail to reject the null hypothesis $p = 0$ for the population correlation. The difference between 0.16 and 0.60, which is quite meaningful in terms of degree of dependence, is thus one that does not permit a discrimination between the hypotheses of perfect dependence and perfect independence. Moreover, the confidence intervals with both $r = 0.16$ and $r = 0.60$ exceed the upper limit value of +1 for the population correlation, which means that, with a small sample of 10 observations, only a very poor approximation to a typically skew distribution can be obtained. As the sample size increases, the problem of non-normality of $r$ and bias in $s_r$ tends to become less perceptible.
For $n = 20$, both confidence intervals for $\rho$ are correctly within the limit values $[-1, 1]$. $r = 0.16$ leads to the rejection of $\rho = 1$ but not of $\rho = 0$, and $r = 0.60$ rejects both the hypotheses $\rho = 0$ and $\rho = 1$. Convergence is slower for higher values of $r$. When $r = 0.99$, only a sample of size $n \geq 36$ permits, correctly, the rejection of the null hypothesis $\rho = 1$ and provides confidence intervals within the bounds $[-1, 1]$. Despite these correct results observed empirically for relatively small sample sizes like $n = 20$ and $n \geq 36$, it is however known from theoretical considerations that the distribution of $r$ tends to normality very slowly (Kendall and Stuart, 1977). Therefore the values obtained for these confidence intervals are nevertheless likely to entail a considerable amount of imprecision.

All these considerations cast serious doubts on the adequacy of $r$ and its estimated standard error $s_r$ in drawing conclusions regarding $\rho$ in finite samples.

An alternative technique, which does not involve the bias deriving from a direct estimate of the sampling error $s_r$, and does not rely on the assumption of normality for the distribution of $r$, is based on the transformation of the distribution function of the sample Pearson correlation coefficient into a "Student's" $t$-distribution. This seems a more appropriate approach for testing if a Pearson correlation $r$ estimated with a small sample is significantly different from some theoretical value of the population $\rho$. Under the particular null hypothesis $\rho = 0$ (Kendall and Stuart, 1977, p.416, §16.28), the distribution of the Pearson correlation $r$ can be obtained indirectly by putting:

$$t = \left[ \frac{(n - 2)r^2}{(1 - r^2)} \right]^{1/2},$$

which follows an exact $t$-distribution with $v = (n - 2)$ degrees of freedom, for any $n$. This $t$-transformation of $r$ can be used to construct tests of the null hypothesis $\rho = 0$ against the alternative hypothesis $\rho \neq 0$. 

71
An analogous $t$-transformation of $r$ can be applied for testing the significance of the deviation of a sample Pearson correlation from some hypothetical value of $\rho$ other than zero. Samiuddin (1970) showed that if equation (3.6) is generalized to:

$$ t = (r - \rho) \left[ \frac{\frac{1}{2}}{(n - 2)(1 - \rho^2)} \right]^{1/2}, \tag{3.7} $$

$t$ remains approximately distributed in "Student's" $t$ form with $v = (n - 2)$ degrees of freedom, for $\rho \neq 0$ and $n \geq 8$. Note that equation (3.7) reduces to equation (3.6) when $\rho = 0$. The general expression (3.7), therefore, can be used both to construct tests of the null hypothesis $\rho = 0$ against the alternative $\rho \neq 0$ and for tests of non-zero cases, when the null and alternative hypotheses are $\rho = \rho_0$ and $\rho \neq \rho_0$ respectively. Alternatively, equation (3.7) can be applied to construct confidence intervals for $\rho$, given that the $t$-distribution remains approximately valid over a range of values of $|\rho|$ which includes also relatively large values.

The approach based on $t$-transformations overcomes the difficulty of directly estimating the standard error of $r$, but it still relies in some degree on the asymptotic properties of its distribution in large samples, especially for large values of $|\rho|$. I therefore consider also a different transformation of the Pearson correlation coefficient, first introduced by Fisher (1921) and subsequently improved by Hotelling (1953). The so-called *Fisher's z-transformation* provides a function of the Pearson correlation $r$ having a distribution which approaches normality with great rapidity and a variance nearly independent of the population correlation $\rho$. This makes the transformation to $z$ particularly useful for testing hypotheses about the population $\rho$ and in constructing confidence intervals for $\rho$, even with very small samples. The $z$-transformation of $r$ is obtained by putting (Fisher, 1921):
which is easily done using a table of the transformation like, for example, the one provided by Fisher and Yates (1963, p.63, Table VIII). Fisher (1950) described three major advantages of \( z \) with respect to \( r \): (i) unlike \( r \), the standard error of \( z \) is practically independent of \( \rho \); (ii) the distribution of \( r \) is non-normal even in large samples if \( \rho \) is large, whereas \( z \) tends rapidly to normality for any \( \rho \); and (iii) the distribution of \( r \) changes its form rapidly as \( \rho \) is changed, making it hopeless to adjust for skewness, whereas because of the nearly constant form of the distribution of \( z \), the accuracy of the tests using \( z \) can be improved with small adjustments. From Hotelling (1953), we have the following expressions for the mean and the variance of \( z \):

\[
E(z) = \zeta + \frac{\rho}{2(n-1)} \left[ 1 + \frac{5 + \rho^2}{4(n-1)} \right] + O(n^{-3}),
\]

\[
\sigma_z^2 = \frac{1}{n-1} \left[ 1 + \frac{4 - \rho^2}{2(n-1)} + \frac{22 - 6\rho^2 - 3\rho^4}{6(n-1)^2} \right] + O(n^{-4}).
\]

Given asymptotic normality of \( r \), by the Mann-Wald theorem \( z \) is also asymptotically normal. And since the coefficient of skewness and the excess of kurtosis are small even for moderate \( n \), the distribution of \( z \) can be regarded as normal with mean and variance approximately equal to \( \zeta = \tanh^{-1} \rho \) and \( 1/(n - 3) \) respectively (Hotelling, 1953, p.218). These simple formulae are approximations and their closeness depends on the actual value of \( \rho \) and on \( n \). The normal approximation for \( z \) above is generally recognized as being remarkably accurate when \(|\rho| \) is moderate, but not as accurate when \(|\rho| \) is large, even for
large $n$. Moreover, the normalizing and variance-stabilizing properties of $z$ are asymptotic ones and its use in very small samples may entail considerable errors. I therefore adopt the correction for bias in $z$ proposed by Hotelling (1953, p.219) and compute the modified formula:

$$z' = z - \frac{r}{2n - 5},$$

(3.11)

which provides a statistic more exactly normally distributed with mean $\zeta$ than $z$, for any $\rho$ and even when $n$ is small. An improved approximation for an estimate of the variance of $z$ independent of $\rho$ is also provided (Hotelling, 1953, p.220):

$$s^2_z = \frac{1}{n - \frac{8}{3}}.$$  

(3.12)

This transformation of $r$ can be used to construct tests of the null hypothesis of perfect linear independence between variates, $\rho = 0$, against the alternative hypothesis $\rho \neq 0$. Under the null $\rho = 0$, $z' \sim N(0, 1/(n - 8/3))$ even in small samples. Given the near independence of the distribution of $z'$ from $\rho$, the $z$-transformation can be applied also for testing whether $r$ is significantly different from theoretical values of $\rho$ other than zero. Equations (3.11) and (3.12) and the assumption of normality can hence be used to construct tests of the null hypothesis $\rho = \rho_0$ against the alternative hypothesis $\rho \neq \rho_0$. For example, under the null $\rho = 0.90$, $z' \sim N(1.472, 1/(n - 8/3))$ even in small samples.
3.2.2 The Spearman Rank Correlation

The Spearman correlation coefficient is a nonparametric statistic which measures the degree of association between two random variables when their distribution is unknown. It is based on the ranks or order of the observations for the variables and was first developed by the psychologist Charles Spearman (1904). Consider the Spearman correlation $r_s$ of a random sample of size $n$ from a bivariate population with correlation $\rho_s$. It is defined as:

$$r_s = 1 - \frac{6 \sum_{i=1}^{n} d_i^2}{n(n^2 - 1)}, \quad (3.13)$$

where $d_i$ denotes the difference between the ranks of the $i$-th observations for the two variates.

An early attempt to define a procedure for testing the significance of $r_s$ was made by Olds (1949). For samples of size $n > 20$ and under the null hypothesis of no association $\rho_s = 0$, Olds suggested to approximate the sampling distribution of $r_s$ by a normal curve with mean zero and variance $\sigma_{r_s}^2 = 1/(n - 1)$. An approximate test can thus be based on the transformation of $r_s$ as:

$$z_r = r_s \sqrt{n - 1}, \quad (3.14)$$

which follows an asymptotically standard normal distribution. A more accurate test of significance was proposed later by Zar (1972), who considers the following transformation of $r_s$:
\[ t = \frac{r_s}{\sqrt{(1 - r_s^2)/(n - 2)}} \]  

(3.15)

where \( t \) has an almost exact "Student's" \( t \)-distribution with \( v = (n - 2) \) degrees of freedom for samples of more than 100 observations and, again, under the hypothesis of no association.

In the same article, Zar also proposed a distribution-free test of association for samples of size \( n \leq 100 \). The test can be obtained by referring \( r_s \) to Zar's distribution table (Zar, 1972, p.579) and rejecting the null hypothesis of no association for large values. This represents the most complete table currently available for \( r_s \) and contains critical values of the Spearman rank correlation for various sample sizes between 4 and 100 and for nine different levels of significance (\( \alpha = 0.50, 0.20, 0.10, 0.05, 0.02, 0.01, 0.005, 0.002, 0.001 \)).

As already observed, a clear understanding of the behaviour of asymptotic distributions in small samples is crucial for my future applications of these theoretical results. For example, Gittleman and Wolff (1993) calculate Spearman correlations from samples of size between \( n = 10 \) and \( n = 20 \), for the various sets of industry wage differentials they consider.

Distribution theory of the Spearman rank correlation under the hypothesis of association is a problem not yet completely solved. The \( z \)-transformation in equation (3.14), the \( t \)-transformations in equation (3.15), and Zar's table can be used, therefore, only to construct tests of the null hypothesis \( \rho_s = 0 \) against the alternative hypothesis \( \rho_s \neq 0 \). Tests for the significance of the deviation of a sample Spearman correlation \( r_s \) from hypothetical values of the population \( \rho_s \) other than zero are, at the present stage, impossible.

3.2.3 The Coefficient of Concordance

To evaluate the degree of agreement among a set of \( m \) variates ranking \( n \) observations according to some specific characteristic, Kendall and Smith (1939) suggested the following measure of concordance:
where $R_i$ is the sum of the ranks assigned to the $i$-th observation for the $m$ variables. Since the average rank across observations for any one variable is $(1 + 2 + ... + n)/n = n(n + 1)/2$, if the ranks assigned to the $i$-th observation were equal to the average for all $m$ variables, the sum of the ranks for observation $i$ would be $m(n + 1)/2$. The numerator of the ratio appearing in equation (3.16), therefore, represents the sum of squares of the deviations of the total of the ranks assigned to each observation from the mean. $W$ can vary from 0 to 1: 0 represents no "community of ranking" among the $m$ variates and 1 represents perfect agreement (Kotz and Johnson, 1982).

Although the coefficient of concordance and the Spearman correlation coefficient are both rank statistics, they are quite different measures. While the Spearman correlation is based on the difference between observed ranks ($d_i$), the coefficient of concordance considers the difference between observed ranks and the mean rank ($R_i - m(n + 1)/2$). Moreover, differences in the two formulae imply that the coefficient of concordance has the range $[0, 1]$, while the Spearman correlation has the range $[-1, 1]$. Therefore, the coefficient of concordance does not reduce to the Spearman correlation when $m = 2$.

The sample distribution of $W$ is rather complicated to derive (Wood, 1970), but if one wants to test hypotheses about the degree of agreement in the population, a transformation of $W$ into an $F$-statistic can be applied. Kendall (1962) showed that, under the null hypothesis of no community of ranking among the $m$ variates in the population, $\omega = 0$, the distribution of:

$$W = 12 \frac{\sum_{i=1}^{m} R_i - m(n + 1)^2}{m^2 n(n^2 - 1)}$$

(3.16)
\[ F = \frac{(m - 1)W}{1 - W} \]  

(3.17)

is approximately a Fisher's F-distribution with degrees of freedom \( v_1 = n - 1 - 2/m \) and \( v_2 = (m - 1)v_1 \). If \( W \) is not significant, this indicates that it is unjustified to attempt to find a common or "pooled" estimate of the "true" ranking, because there is insufficient evidence that this exists. If \( W \) is significant, it is reasonable to estimate a supposed "true" ranking of the \( n \) observations. This is done by ranking them according to the sum of ranks assigned to each observation, the one with the smallest sum being ranked first and so on (Kotz and Johnson, 1982). The F-transformation of \( W \) can therefore be used to construct a test of the null hypothesis of no concordance of rankings in the population, \( \omega = 0 \), against the alternative hypothesis \( \omega > 0 \), that some concordance exists and a common "true" ranking can be estimated through the sum of ranks. Note that the null hypothesis of no concordance refers to the joint concordance of rankings among all \( m \) variables. In particular, \( \omega = 0 \) does not imply a zero concordance between any possible pair of variables.

An alternative approach to the same test of significance of \( W \) consists in the transformation of \( W \) into a \( \chi^2 \) statistic. Daniel (1978) showed that, for large samples, the distribution of \( m(n - 1)W \) is approximately \( \chi^2 \) with \( v = n - 1 \) degrees of freedom. This is the approach adopted by Gittleman and Wolff (1993) for their tests of the significance of coefficients of concordance. The method, however, is only asymptotically valid and may entail a considerable problem of accuracy in small samples. This is a relevant issue in the case of Gittleman and Wolff's results, because their sample sizes range from \( n = 8 \) to

---

\[ m(N + 1) \]

for any observation. This condition in fact excludes the possibility that the sum over any two variables of the ranks assigned to each observation is equal to \( \frac{2(N + 1)}{2} = N + 1 \), which would be the condition for generalized pair-wise zero concordances in the population.

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9 In a finite population of size \( N \) and under the null hypothesis \( \omega = 0 \), the sum over the \( m \) variables of the ranks assigned to each observation is equal to \( m \) times the mean rank, \( \frac{m(N + 1)}{2} \), for any observation. This condition in fact excludes the possibility that the sum over any two variables of the ranks assigned to each observation is equal to \( 2(N + 1) = N + 1 \), which would be the condition for generalized pair-wise zero concordances in the population.
\( n = 20 \) for the various sets of industry wage differentials considered. In Sections 3.3 and 3.4 I will therefore apply the more accurate \( F \)-transformation.

Little is known about the distribution of \( W \) in the non-null case. Wood (1970) investigated some of the properties of this distribution under the assumption that the rankings have been generated by taking \( n \) observations from an \( m \)-variate normally distributed population with all the Spearman correlations, calculated for the \( {m \choose 2} \) possible pairs of rankings, equal to \( \rho_s \). In this case \( E(W) = \{(m - 1)\rho_s + 1\}/m \) and Wood proposed a variance stabilizing transformation of \( W \) which makes its variance nearly independent of \( \rho_s \).

The lack of knowledge about other aspects of the distribution of \( W \) under the non-null hypothesis, however, does not permit one to test whether \( W \) is significantly different from theoretical values other than zero.

The particular nature and interpretation of the coefficient of concordance might explain why this metric has not become more popular in economic applications. "Concordance" is meant here in a rather weak sense. The larger the number of rankings to be compared, the looser the requirements for a significant concordance. As one can see from equation (3.17), the significance of the coefficient of concordance is highly sensitive to the number of variates considered. Even for relatively small values of \( m \), the value of \( W \) required to reject the null hypothesis of no concordance can be indeed quite small. For example, when \( m = 10 \), even a coefficient of concordance as small as 0.28 is significantly greater than zero at the 1% level, for any sample size \( n \geq 5 \). It is however doubtful whether a value like \( W = 0.28 \) can be regarded as strong enough evidence of the existence of a common "true" ranking, especially in a small sample.

In this Section I have illustrated the statistical properties of the sampling distributions for the three measures of association considered in this Chapter, the Pearson and Spearman correlations and the coefficient of concordance. In the next two Sections, I will use these theoretical results to construct confidence intervals and test hypotheses for the corresponding
population parameters \( \rho, \rho_z \) and \( \omega \). The general purpose of Sections 3.3 and 3.4 is to evaluate whether the general conclusions drawn by Krueger and Summers (1987) and by Gittleman and Wolff (1993) about the stability - over time and across countries - of industry wages in the population are actually consistent with the sample values they find for \( r, r_z \) and \( W \).

In the present context, I am interested in two types of tests. The first is the test of the null hypothesis of no association in the population against the alternative hypothesis of a positive association. The one-tail structure of the test is the appropriate one in this case since "stability" of industry wages is claimed by Krueger and Summers and by Gittleman and Wolff and only a positive association is therefore expected. The second type of test is the test of the null hypothesis of a "strong" (positive) association in the population against the hypothesis of a "weak" (weak positive or any negative) association, which is the relevant alternative in this context since both Krueger and Summers and Gittleman and Wolff claim that stability of industry wages is "strong enough" to justify their conclusions. This again leads to a one-tail structure for the appropriate test.

As we have seen, the first type of test can be readily performed for all three measures of association. Unfortunately, this is not the most interesting test in the case of Krueger and Summers's and Gittleman and Wolff's results. The authors, in fact, do not try to suggest that any degree of positive association would be regarded as supportive evidence. However, failure to reject even the null hypothesis of no association in the population represents a very strong result against the claimed stability of industry wages and therefore I can look at the result for this type of test as a minimum requirement before any further consideration about the "strength" of a positive association. The second type of test is more relevant in the context of Krueger and Summers's and Gittleman and Wolff's results, but it can be implemented only for Pearson correlations. Limited knowledge about the sampling distributions of \( r_z \) and \( W \) in the non-zero case prevents one from conducting such type of test for Spearman correlations and coefficients of concordance. Moreover, it implies a considerable amount of arbitrariness in the choice of the exact null hypothesis to be tested.

This is a consequence of the particular form of the sampling distribution of the Pearson correlation. Its distribution is truncated at -1 and +1 and this implies that the frequency curve tends to collapse into a spike as the population correlation approaches these
extreme values. As a result (see Sub-Section 3.2.1), any observed value of the sample Pearson correlation smaller than 1 leads to the rejection of the null hypothesis of a population correlation equal to 1. Thus, when Krueger and Summers and Gittleman and Wolff claim that stability of industry wages is "strong", they are obviously not implying the existence of a perfect positive association in the population (a population correlation $\rho$ equal to +1 under the null hypothesis) since all their observed sample Pearson correlations are smaller than 1 and a test of the null hypothesis of perfect positive association would trivially reject it in all cases, at any significance level. Similar considerations hold for hypothetical values of the population correlation very close to 1 under the null hypothesis. The sample correlation $r$ would be so narrowly distributed around the hypothetical value under the null that even values of $r$ just slightly smaller than this hypothetical value would imply the rejection of the null hypothesis and so the test would not be particularly meaningful. For example, if we assume that by a "strong" association we mean a population correlation $\rho$ equal to 0.99, even a sample correlation like $r = 0.95$ can lead - in certain circumstances\(^\text{10}\) - to the rejection of the null hypothesis $\rho = 0.99$ of "strong" association. But at the same time $r = 0.95$ can be consistent, at the 1% significance level, with a population correlation $\rho$ equal to 0.98 and so be indeed indicative of a "strong" association in the population, even if not as strong as 0.99. Hypothetical values of $\rho$ too close to 1 make the test trivial and the null hypothesis of "strong" association too easily rejected to be meaningful.

So the crucial question is, how "strong" is a "strong association" in statistical terms? How should one choose an appropriate null hypothesis to test for a "strong" association in the population? This kind of ambiguity typically surrounds a measure of association like the Pearson correlation for the reasons just illustrated. At various stages, Krueger and Summers and Gittleman and Wolff seem to regard values like 0.80 or 0.90 as especially meaningful critical values\(^\text{11}\). But elsewhere they extend the same judgement to a value as small as

\(^{10}\) The example is taken from Table 3.7 in Section 3.4, for the sample correlation between industry wages in France and Japan, in a sample of size $n = 20$.

\(^{11}\) For example Krueger and Summers write, "The industry wage structure for all industries has remained remarkably constant since 1915, with [Pearson] correlations with the wage structure in 1984 ranging from 0.76 to 0.98." (Krueger and Summers, 1987, p.22). And also, "In general, the pattern of relative wages is remarkably similar across countries [...]. The [Pearson] correlations are quite high, typically between 0.7 and 0.9. [...] Eight of the 13 correlations between the US and other countries are above 0.8 [...]." (Krueger and Summers, 1987, 81)
0.60\textsuperscript{12}. The point is that the authors rely exclusively on the specific values of their sample statistics in concluding that the degree of association among the various industry wage structures is "strong". But in doing so, they fail to recognize that each value of the sample measures of association they find is in fact consistent with a whole range of values of the corresponding population parameters, possibly including zero and/or very high positive values. And in a small sample, a value like 0.60 for any measure of association can indeed be compatible even with the null hypothesis of no association at all in the population (as we will see later). So higher values are probably more suitable as indicators of a "strong" association. And in order to take into account the small size of the samples involved, we might be tempted to look at a high value like 0.90 as an appropriate critical value.

To summarize, an observed value of a sample measure of association that rejects the null hypothesis of zero association in the population in the first type of test \textit{and} - when the test is possible - fails to rejects the null hypothesis of a degree of association in the population equal to a large (but not too large) value like 0.90 in the second type of test can be regarded as evidence of strong positive association, in rigorous statistical terms. However, in evaluating the results of my later testing procedures, it is worth acknowledging that 0.90 is as good (or as bad) a critical value as many others and that, in the end, it is a matter of the personal interpretation we give of what a "strong" association should be.

In the next two Sections, hypothesis testing is conducted both at the conventional 1\% significance level and at the more rigorous 0.5\% significance level. The latter will be considered in all tests in order to take into account the problem of precision that arises from having very small samples of observations for aggregate industry wages.

\textsuperscript{12} For example Krueger and Summers write, "[...] the [Pearson] correlation is still greater than 0.60 between relative wages in 1900 and 1984." (Krueger and Summers, 1987, p.22). Gittleman and Wolff write, "[...] the [Pearson] correlation coefficients are quite high (for example in 1970, ranging from 0.60 to 0.90) [...]" (Gittleman and Wolff, 1993, p.304). And also, "The coefficients [of concordance] all exceed 0.6, and in most cases exceed 0.7 and reach as high as 0.8." (Gittleman and Wolff, 1993, p.304).
3.3 Stability of Wage Structures over Time

The results that I discuss in this and in the following Section are derived from two studies of the inter-industry wage structure based on aggregate average industry wage data, the first by Krueger and Summers (1987) and the second by Gittleman and Wolff (1993). One of the aspects considered by these authors is the inter-temporal stability of industry wage differentials. Both studies reach the conclusion that the industrial wage structures appear remarkably stable over time for all the countries considered. In the remainder of this Section I will try to evaluate in statistically rigorous terms the correctness of this claim.

Krueger and Summers (1987, pp.22-24) evaluate the stability of the wage structure over time in the United States by comparing average wages in nine major industries for selected years between 1980 and 1900 with wages in 1984. The original data are derived from Historical Statistics of the U.S. and various issues of the Survey of Current Business. The variable considered is the logarithm of average annual earnings by industry of full-time equivalent employees. The industries are agriculture, manufacturing, mining, construction, transportation, communications, wholesale and retail trade, FIRE (finance, insurance and real estate), and services. Their results are reported in the first two columns of Table 3.1. Pearson correlations of log average annual earnings are proposed by Krueger and Summers to suggest that the industry wage structure for all industries has remained remarkably stable since 1920, with correlations with the wage structure in 1984 ranging from 0.76 to 0.98. Before 1920 the pattern of industry wages appears less similar to the 1984 industry wage structure, but the correlations are still above 0.60 for all years up to 1900. Taking into account changes in industry definitions and sampling errors, this seems to imply, according to the authors, that the structure of relative industry wages changed only moderately over a very long time interval (Krueger and Summers, 1987, p.23).

---

13 When earnings structures of any type are compared, it is a common practice to consider the logarithm of earnings rather than absolute earnings. This is due to the fact that the frequency distribution of earnings across the population is approximately log-normal, i.e. earnings tend to be normally distributed in the logarithms. If comparisons are made by computing Pearson correlations between earnings structures, one must be able to assume that the underlying population is normally distributed. This condition is, therefore, more exactly satisfied by the logarithm of earnings. The logarithmic transformation tends to give slightly higher Pearson correlation coefficients, through attenuating the influence of large earnings (Atkinson et al., 1992). Spearman rank correlations and coefficients of concordance are instead unaffected since the logarithmic transformation is a monotone transformation, which does not alter the ranking of values.
TABLE 3.1

Krueger and Summers's industry wage structure over time in the U.S.: estimated Pearson correlation coefficients, respective standard errors and two-sided 99% confidence intervals, for log average annual earnings of full-time equivalent employees, in nine major industries.*

<table>
<thead>
<tr>
<th>Year</th>
<th>Correlation with 1984</th>
<th>Standard error</th>
<th>Two-sided 99% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>1984</td>
<td>1.000</td>
<td>0.000</td>
<td>1.000 - 1.000</td>
</tr>
<tr>
<td>1980</td>
<td>0.984</td>
<td>0.016</td>
<td>0.942 - 1.026</td>
</tr>
<tr>
<td>1975</td>
<td>0.961</td>
<td>0.039</td>
<td>0.861 - 1.061</td>
</tr>
<tr>
<td>1970</td>
<td>0.909</td>
<td>0.084</td>
<td>0.693 - 1.125</td>
</tr>
<tr>
<td>1965</td>
<td>0.898</td>
<td>0.093</td>
<td>0.659 - 1.137</td>
</tr>
<tr>
<td>1960</td>
<td>0.893</td>
<td>0.097</td>
<td>0.644 - 1.142</td>
</tr>
<tr>
<td>1955</td>
<td>0.893</td>
<td>0.097</td>
<td>0.644 - 1.142</td>
</tr>
<tr>
<td>1950</td>
<td>0.866</td>
<td>0.117</td>
<td>0.565 - 1.167</td>
</tr>
<tr>
<td>1945</td>
<td>0.891</td>
<td>0.098</td>
<td>0.638 - 1.144</td>
</tr>
<tr>
<td>1940</td>
<td>0.836</td>
<td>0.137</td>
<td>0.482 - 1.190</td>
</tr>
<tr>
<td>1935</td>
<td>0.793</td>
<td>0.164</td>
<td>0.370 - 1.216</td>
</tr>
<tr>
<td>1930</td>
<td>0.761</td>
<td>0.182</td>
<td>0.291 - 1.231</td>
</tr>
<tr>
<td>1925</td>
<td>0.801</td>
<td>0.159</td>
<td>0.390 - 1.212</td>
</tr>
<tr>
<td>1920</td>
<td>0.807</td>
<td>0.156</td>
<td>0.406 - 1.208</td>
</tr>
<tr>
<td>1915</td>
<td>0.627</td>
<td>0.243</td>
<td>-0.001 - 1.255</td>
</tr>
<tr>
<td>1910</td>
<td>0.604</td>
<td>0.252</td>
<td>-0.046 - 1.254</td>
</tr>
<tr>
<td>1905</td>
<td>0.636</td>
<td>0.240</td>
<td>0.017 - 1.255</td>
</tr>
<tr>
<td>1900</td>
<td>0.616</td>
<td>0.248</td>
<td>-0.023 - 1.255</td>
</tr>
</tbody>
</table>

* Source: Krueger and Summers (1987, p.24, Table 2.2).
* The sample size for the estimate of the Pearson correlation coefficients is n = 9. Industries include: agriculture, manufacturing, mining, construction, transportation, communications, wholesale and retail trade, FIRE, and services.
* Calculated using equation (3.5), Sub-Section 3.2.1.
* Approximate two-sided 99% confidence intervals, under the assumption that r follows an asymptotically normal distribution.

FIGURE 3.2

Krueger and Summers's industry wage structure over time in the U.S.: Pearson correlation coefficients with 1984 and two-sided 99% confidence intervals.
Given the fact that the Pearson correlations presented by Krueger and Summers are based on very small samples of only nine pairs of observations - one for each industry aggregate - I want to test accurately their statistical significance. This high level of aggregation in the industry classification chosen by Krueger and Summers and the consequent small size of their samples are recurrent features of this type of inter-temporal comparisons among industry wage structures. Official industry classifications used in statistical publications are likely to change over time, both because of improvements in survey methods and because of the necessity to reflect ongoing changes in the structure of economic activities. In order to compare industry wages based on heterogeneous industry classifications for different years, one needs to define a common classification and this is usually achieved only at the cost of increasing the level of aggregation of the industry classification. The researcher, therefore, faces a trade-off between the length of the time span considered and the number of industries kept in the common classification. The longer the time period, the less detailed the industry classification and the smaller the size of the samples available for inter-temporal comparisons of industry wage structures.

A first way to address the issue of statistical significance is to construct two-sided 99% confidence intervals for the population Pearson correlation coefficients using the first procedure illustrated in Sub-Section 3.2.1. The results obtained by relying on the assumption of asymptotic normality of $r$, applying equation (3.5) to calculate its standard error $s_r$, and using it to construct two-sided 99% confidence intervals for the population $\rho$ are presented in the last two columns of Table 3.1 and graphed in Figure 3.2.

We can immediately notice the extreme width of the confidence intervals in many cases. For example, with a sample of only 9 observations, we have a 99% confidence interval of about 0.64 for a Pearson correlation coefficient equal to 0.616 and a 99% confidence interval of about 0.35 for a correlation coefficient equal to 0.836. As we have seen in Sub-Section 3.2.1, since the estimated standard error $s_r$ is a monotone decreasing function of the sample correlation coefficient $r$ - for positive values of the sample correlation - it tends to zero as the Pearson correlation approaches 1 in 1984. We also observe that we are unable to reject the null hypothesis of perfect positive dependence for all the values of the Pearson correlation at the 1% significance level, since the value $\rho = 1$ is enclosed in all confidence intervals. At the same time, however, for some values of the Pearson correlation
- the coefficients for 1915, 1910, and 1900 - we are unable to reject the null hypothesis of a population correlation equal to zero at the 1% significance level. The serious limitations encountered by this method in hypothesis testing with small samples can be seen in the last column of Table 3.1. from the fact that the two-sided 99% confidence intervals thus derived all exceed the upper limit value of +1 for the population Pearson correlation and that even a sample correlation as \( r = 0.616 \) fails to reject the null hypothesis \( \rho = 1 \). For the reasons explained in Sub-Section 3.2.1, these incorrect results are certainly a consequence of the extremely moderate sample size and the resulting non-normality of \( r \) and bias in \( s_r \). As previously observed, in fact, any value of \( r \) smaller than 1 should lead to the rejection of the null hypothesis \( \rho = 1 \), at any significance level.

I also consider, therefore, tests of significance based on the \( t \)- and \( z \)-transformation of the Pearson correlation \( r \) illustrated in Sub-Section 3.2.1. Two different hypotheses about the population \( \rho \) are to be tested: the null hypothesis of no dependence between industry wage structures, \( \rho = 0 \), against the alternative hypothesis of a positive dependence, \( \rho > 0 \); and the null hypothesis of a "high" positive dependence between industry wage structures, \( \rho = \rho_0 \), where \( \rho_0 \) is some (positive and large) critical value of the correlation, against the alternative hypothesis of a "low" dependence, \( \rho < \rho_0 \). The former test implies a statistical appraisal of the existence in the population of some linear dependence between wage structures, while the latter test tries to evaluate whether the degree of positive dependence is high enough to justify the claim of the authors about a strong stability of wage structures over time. In order to avoid the arbitrariness of the choice of a critical value \( \rho_0 \), I will present confidence intervals for the whole ranges of values of \( \rho \) consistent with the observed sample correlations at a specified confidence level, rather than the results of specific hypothesis tests. For the reasons illustrated in the previous Section, some of my considerations will nevertheless refer to \( \rho_0 = 0.90 \) as the relevant critical value for the appraisal of a high positive dependence between industry wage structures. However, the confidence intervals can readily be used to test for high positive dependence with reference to any alternative critical value.
Table 3.2 gives the outcomes for the confidence intervals for $\rho$ based on the $t$- and $z$-transformation of $r$. The third and the fourth columns contain the confidence intervals derived by applying Samiuddin's $t$-transformation. Equation (3.7) is inverted in order to express $\rho$ as a function of $r$ and of the appropriate critical value of the "Student's" $t$. The lower and upper bounds of the intervals are hence calculated as:

$$
\rho_{\text{lower}(-), \text{upper}(+)} = \frac{(n-2)r \pm t_{\text{crit} (n-2)}(1-r^2)\sqrt{n-2} + t_{\text{crit} (n-2)^2}}{(n-2) + t_{\text{crit} (n-2)}^2(1-r^2)}. 
$$

(3.18)

Since I want to conduct one-tail hypothesis tests for $\rho$ at the 1% and 0.5% significance level, each confidence interval $\rho_{\text{lower}} < \rho < \rho_{\text{upper}}$ should actually be viewed as a couple of one-sided intervals at the 99% (third column) or 99.5% (fourth column) confidence level. So $\rho > \rho_{\text{lower}}$ is the one-sided 99% (99.5%) confidence interval which I can use for the one-tail test of the null hypothesis $\rho = 0$ against the alternative $\rho > 0$ at the 1% (0.5%) significance level; $\rho < \rho_{\text{upper}}$ is the one-sided 99% (99.5%) confidence interval which I can use for the one-tail test of the null hypothesis $\rho = \rho_0$ against the alternative $\rho < \rho_0$ at the 1% (0.5%) significance level.

The last four columns of Table 3.2 give the values for the Fisher's $z$-transformation with Hotelling's correction $z'$ and its estimated standard error $s_z'$, calculated through equations (3.11) and (3.12), and the confidence intervals for $\rho$ obtained from $z'$ and $s_z'$ as follows. First I consider the confidence interval for $\zeta$ - the population parameter of which $z'$ is a sample estimate - given by $\zeta = z' \pm z_{\text{crit}}s_z'$, where $z_{\text{crit}}$ is the appropriate critical value of the standard normal variable. Equation (3.8) defines $\zeta$ as $\zeta = \frac{1}{2} \log \frac{1 + \rho}{1 - \rho}$. From the expression for the confidence interval for $\zeta$ I can then derive the corresponding confidence
TABLE 3.2

Krueger and Summers's industry wage structure over time in the U.S.: estimated Pearson correlation coefficients and confidence intervals based on t and z transformations, for log average annual earnings of full-time equivalent employees, in nine major industries.

<table>
<thead>
<tr>
<th>Year</th>
<th>$r^*$</th>
<th>One-sided 99% confidence interval</th>
<th>One-sided 99.5% confidence interval</th>
<th>$z^*$</th>
<th>$z_{.05}$</th>
<th>One-sided 99% confidence interval</th>
<th>One-sided 99.5% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>1984</td>
<td>1.000</td>
<td>$1 &lt; p &lt; 1$</td>
<td>$1 &lt; p &lt; 1$</td>
<td>$\infty$</td>
<td>0.397</td>
<td>$1 &lt; p &lt; 1$</td>
<td>$1 &lt; p &lt; 1$</td>
</tr>
<tr>
<td>1980</td>
<td>0.984</td>
<td>0.893 &lt; $p$ &lt; 0.998</td>
<td>0.866 &lt; $p$ &lt; 0.998</td>
<td>2.334</td>
<td>0.397</td>
<td>0.887 &lt; $p$ &lt; 0.997</td>
<td>0.864 &lt; $p$ &lt; 0.998</td>
</tr>
<tr>
<td>1975</td>
<td>0.961</td>
<td>0.756 &lt; $p$ &lt; 0.994</td>
<td>0.700 &lt; $p$ &lt; 0.996</td>
<td>1.885</td>
<td>0.397</td>
<td>0.744 &lt; $p$ &lt; 0.993</td>
<td>0.697 &lt; $p$ &lt; 0.994</td>
</tr>
<tr>
<td>1970</td>
<td>0.999</td>
<td>0.500 &lt; $p$ &lt; 0.986</td>
<td>0.405 &lt; $p$ &lt; 0.989</td>
<td>1.452</td>
<td>0.397</td>
<td>0.483 &lt; $p$ &lt; 0.983</td>
<td>0.404 &lt; $p$ &lt; 0.986</td>
</tr>
<tr>
<td>1965</td>
<td>0.898</td>
<td>0.454 &lt; $p$ &lt; 0.985</td>
<td>0.354 &lt; $p$ &lt; 0.988</td>
<td>1.393</td>
<td>0.397</td>
<td>0.437 &lt; $p$ &lt; 0.981</td>
<td>0.353 &lt; $p$ &lt; 0.984</td>
</tr>
<tr>
<td>1960</td>
<td>0.893</td>
<td>0.433 &lt; $p$ &lt; 0.984</td>
<td>0.331 &lt; $p$ &lt; 0.987</td>
<td>1.368</td>
<td>0.397</td>
<td>0.416 &lt; $p$ &lt; 0.980</td>
<td>0.331 &lt; $p$ &lt; 0.983</td>
</tr>
<tr>
<td>1955</td>
<td>0.893</td>
<td>0.433 &lt; $p$ &lt; 0.984</td>
<td>0.331 &lt; $p$ &lt; 0.987</td>
<td>1.368</td>
<td>0.397</td>
<td>0.416 &lt; $p$ &lt; 0.980</td>
<td>0.331 &lt; $p$ &lt; 0.983</td>
</tr>
<tr>
<td>1950</td>
<td>0.866</td>
<td>0.331 &lt; $p$ &lt; 0.980</td>
<td>0.221 &lt; $p$ &lt; 0.984</td>
<td>1.250</td>
<td>0.397</td>
<td>0.315 &lt; $p$ &lt; 0.974</td>
<td>0.223 &lt; $p$ &lt; 0.979</td>
</tr>
<tr>
<td>1945</td>
<td>0.891</td>
<td>0.425 &lt; $p$ &lt; 0.984</td>
<td>0.323 &lt; $p$ &lt; 0.987</td>
<td>1.358</td>
<td>0.397</td>
<td>0.408 &lt; $p$ &lt; 0.979</td>
<td>0.322 &lt; $p$ &lt; 0.983</td>
</tr>
<tr>
<td>1940</td>
<td>0.836</td>
<td>0.231 &lt; $p$ &lt; 0.975</td>
<td>0.115 &lt; $p$ &lt; 0.980</td>
<td>1.143</td>
<td>0.397</td>
<td>0.216 &lt; $p$ &lt; 0.968</td>
<td>0.119 &lt; $p$ &lt; 0.974</td>
</tr>
<tr>
<td>1940</td>
<td>0.793</td>
<td>0.106 &lt; $p$ &lt; 0.968</td>
<td>0.013 &lt; $p$ &lt; 0.974</td>
<td>1.018</td>
<td>0.397</td>
<td>0.094 &lt; $p$ &lt; 0.960</td>
<td>0.005 &lt; $p$ &lt; 0.967</td>
</tr>
<tr>
<td>1935</td>
<td>0.761</td>
<td>0.026 &lt; $p$ &lt; 0.962</td>
<td>0.009 &lt; $p$ &lt; 0.970</td>
<td>0.940</td>
<td>0.397</td>
<td>0.016 &lt; $p$ &lt; 0.953</td>
<td>0.008 &lt; $p$ &lt; 0.961</td>
</tr>
<tr>
<td>1925</td>
<td>0.801</td>
<td>0.128 &lt; $p$ &lt; 0.969</td>
<td>0.009 &lt; $p$ &lt; 0.975</td>
<td>1.040</td>
<td>0.397</td>
<td>0.115 &lt; $p$ &lt; 0.961</td>
<td>0.016 &lt; $p$ &lt; 0.968</td>
</tr>
<tr>
<td>1920</td>
<td>0.807</td>
<td>0.145 &lt; $p$ &lt; 0.970</td>
<td>0.026 &lt; $p$ &lt; 0.976</td>
<td>1.056</td>
<td>0.397</td>
<td>0.131 &lt; $p$ &lt; 0.963</td>
<td>0.032 &lt; $p$ &lt; 0.969</td>
</tr>
<tr>
<td>1915</td>
<td>0.627</td>
<td>-0.232 &lt; $p$ &lt; 0.936</td>
<td>-0.341 &lt; $p$ &lt; 0.950</td>
<td>0.688</td>
<td>0.397</td>
<td>-0.232 &lt; $p$ &lt; 0.923</td>
<td>-0.323 &lt; $p$ &lt; 0.937</td>
</tr>
<tr>
<td>1910</td>
<td>0.614</td>
<td>-0.266 &lt; $p$ &lt; 0.932</td>
<td>-0.374 &lt; $p$ &lt; 0.946</td>
<td>0.653</td>
<td>0.397</td>
<td>-0.265 &lt; $p$ &lt; 0.918</td>
<td>-0.354 &lt; $p$ &lt; 0.932</td>
</tr>
<tr>
<td>1905</td>
<td>0.636</td>
<td>-0.217 &lt; $p$ &lt; 0.938</td>
<td>-0.328 &lt; $p$ &lt; 0.951</td>
<td>0.703</td>
<td>0.397</td>
<td>-0.218 &lt; $p$ &lt; 0.926</td>
<td>-0.310 &lt; $p$ &lt; 0.939</td>
</tr>
<tr>
<td>1900</td>
<td>0.616</td>
<td>-0.248 &lt; $p$ &lt; 0.934</td>
<td>-0.357 &lt; $p$ &lt; 0.948</td>
<td>0.671</td>
<td>0.397</td>
<td>-0.248 &lt; $p$ &lt; 0.921</td>
<td>-0.338 &lt; $p$ &lt; 0.935</td>
</tr>
</tbody>
</table>

* Source: Krueger and Summers (1987, p. 24, Table 2.2).

* The sample size for the estimate of the Pearson correlation coefficients is $n = 9$. Industries include: agriculture, manufacturing, mining, construction, transportation, communications, wholesale and retail trade, FIRE, and services.

* Confidence interval for the one-tail test of the null hypothesis $H_0$: $p = 0$ against the alternative $H_1$: $p > 0$ (positive correlation) at the 1% level, or for the one-tail test of the null hypothesis $H_0$: $p = 0$ against the alternative $H_1$: $p < 0$ (negative correlation) at the 1% level.

* Confidence interval for the one-tail test of the null hypothesis $H_0$: $p = 0$ against the alternative $H_1$: $p > 0$ (positive correlation) at the 0.5% level, or for the one-tail test of the null hypothesis $H_0$: $p = 0$ against the alternative $H_1$: $p < 0$ (negative correlation) at the 0.5% level.
interval for $p$. This yields the following lower and upper bounds:

$$p_{\text{lower}(-), \text{upper}(+)} = \frac{\exp[2(z' \pm z_{cr} s_{z'})] - 1}{\exp[2(z' \pm z_{cr} s_{z'})] + 1}$$  \hspace{1cm} (3.19)

Again, each confidence interval for $p$ should be viewed as a couple of one-sided intervals at the 99% (seventh column) or 99.5% (eighth column) confidence level.

The two alternative transformations of $r$ provide quite similar results, but we should regard the results based on the $z$-transformation as more accurate given the small size of the samples considered. The null hypothesis of a positive dependence as high as 0.90 cannot be rejected for any Pearson correlation between the 1984 wage structure and the wage structures in all years from 1900 to 1980, both at the 1% and at the 0.5% significance level. At the same time, however, the null hypothesis of total independence in the population cannot be rejected at the 1% significance level for the years between 1900 and 1915 and at the 0.5% significance level also for 1930 and 1935.

This is due to the considerable width of most confidence intervals. With samples of only 9 observations\(^{14}\), 99% confidence intervals range from (-0.10, +0.01)\(^{15}\) around $r = 0.98$ for 1980 to (-0.87, +0.31) around $r = 0.60$ for 1910 or, expressed as percentages of the respective sample correlation $r$, from (-10%, +1%) to (-144%, +52%). The average 99% confidence interval over all observed sample correlations is, in percentage points, (-79%, +21%) around $r$. Intervals at the 99.5% confidence level are obviously even wider. So, for example, even a sample correlation as large as $r = 0.91$ for 1970 is compatible, at the 99% confidence level, both with a true population correlation equal to 0.48 and with a true population correlation equal to 0.98. And the difference between 0.48 and 0.98 is one that

\(^{14}\) The following values refer to the more accurate confidence intervals based on the $z$-transformation (seventh and eighth columns of Table 3.2).

\(^{15}\) Confidence intervals for $p$ are asymmetric with respect to the value of $r$, extending further downwards than upwards.
would seriously affect the conclusions drawn about wage stability over time, since 0.48 is typically indicative of an ambiguous degree of similarity between wage structures, while 0.98 suggests a very strong degree of similarity. In some cases, the plausible population correlations within the intervals include both the value 0 and a high value like 0.90. Samples are so small that for the years between 1900 and 1915, 1930, and 1935 the sampling error overwhelms the estimated correlation $r$ and produces statistical indiscernibility between the hypothesis of total independence and of high positive dependence.

A methodologically similar but more comprehensive analysis of the stability of wage structures over time is proposed by Gittleman and Wolff (1993, pp.298-300). The authors compare aggregate industry differentials over the period 1970-1985, in 14 OECD countries. The original data source is the *International Sectoral Data Base (ISDB)* of the OECD. They consider a measure of industry wage differentials defined as:

$$D_k^h = \ln \left( \frac{w_k^h}{\bar{w}^h} \right),$$

(3.20)

where $w_k^h$ is the average wage in industry $k$ of country $h$ and $\bar{w}^h$ is the average wage in country $h$. The variable $D_k^h$ represents, therefore, the average wage differential of industry $k$ in a certain country with respect to the average wage for the whole economy of the same country. Inter-industry wage differentials are calculated at the most disaggregated level possible. The number of industries in the national samples varies according to the different system of classification of production activities adopted in each country and ranges from a minimum of 10 to a maximum of 20 sectors. The exact number of sectors available for each country are reported in the Tables that follow. For the comparisons of industry wage differentials over time, Gittleman and Wolff use three different measures of association: the Pearson correlation, the Spearman correlation, and the coefficient of concordance. According to the authors, all three measures provide strong evidence that the economy-wide wage structures of all the countries considered have been very stable during the period examined.

I will start evaluating the findings for the Pearson correlation coefficient. Gittleman and Wolff calculate correlations between the 1985 industry wage structure and wage
differentials in 1980, 1975, and 1970 for the 14 countries considered. Their results are reported in the first two columns of Table 3.3. Pearson correlations with 1985 generally tend to fall the further back in time one goes, but they remain quite high in all cases. For 1980, all correlations exceed 0.90; for 1975, 11 of the 14 countries present correlations greater than 0.90 and in the other 3 countries they range between 0.85 and 0.89; for 1970, 6 correlations still exceed 0.90 and 5 are greater than 0.80. The size of the samples examined is somewhat larger than in Krueger and Summers's case, but it never exceeds 20 observations and this may critically affect the significance of the estimated values.

As for Krueger and Summers's results, I first address the question of statistical significance by constructing two-sided 99% confidence intervals for the population Pearson correlations based on the assumption of asymptotic normality of r and on equation (3.5) for its standard error. The estimated standard errors \( s_r \) and the bounds of confidence intervals are given in the third and fourth columns of Table 3.3 and graphed in Figures 3.3, 3.4, and 3.5 for the various pairs of years. Confidence intervals are relatively narrow for the Pearson correlations between the 1985 and the 1980 wage differentials, but they rapidly become much wider as one moves back in previous years. For example, Australia, with a sample of only 10 observations, presents a 99% confidence interval of about 0.11 for a Pearson correlation equal to 0.95 in 1980 and a 99% confidence interval of about 0.23 for a correlation equal to 0.89 in 1970; Sweden, with a larger sample of 20 observations, presents a 99% confidence interval of about 0.03 for a Pearson correlation equal to 0.98 in 1980 and a 99% confidence interval of about 0.12 for a correlation equal to 0.91 in 1970. In all cases, the null hypothesis of a population correlation equal to zero can be rejected at the 1% significance level, while it seems that we are always unable to reject the null hypothesis of perfect positive dependence at the same level of significance. This second outcome, however, is certainly affected by non-normality of r and bias in \( s_r \) due to the moderate sample size. As in the case of Krueger and Summers's results, in fact, all confidence intervals incorrectly exceed the upper limit value of +1.

The results obtained for the more accurate testing procedures based on the \( t- \) and \( z- \)transformations of r are presented in Table 3.4. The Table shows the one-sided 99% and 99.5% confidence intervals for \( p \) derived from the two alternative transformations. Looking at the more exact intervals based on the z-transformation, we can see that the null hypothesis
TABLE 3.3
Gittleman and Wolff's industry wage differentials over time within countries' estimated Pearson correlation coefficients with 1985, respective standard errors and two-sided 99% confidence intervals for all industries

<table>
<thead>
<tr>
<th>Country</th>
<th>Correlation for 1980</th>
<th>Standard error s</th>
<th>Two-sided 99% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.95</td>
<td>0.044</td>
<td>0.836 - 1.064</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.99</td>
<td>0.006</td>
<td>0.974 - 1.006</td>
</tr>
<tr>
<td>Canada</td>
<td>0.98</td>
<td>0.011</td>
<td>0.951 - 1.009</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.96</td>
<td>0.021</td>
<td>0.906 - 1.014</td>
</tr>
<tr>
<td>Finland</td>
<td>0.98</td>
<td>0.011</td>
<td>0.953 - 1.007</td>
</tr>
<tr>
<td>France</td>
<td>0.99</td>
<td>0.006</td>
<td>0.974 - 1.006</td>
</tr>
<tr>
<td>Germany</td>
<td>0.99</td>
<td>0.006</td>
<td>0.976 - 1.004</td>
</tr>
<tr>
<td>Italy</td>
<td>0.98</td>
<td>0.012</td>
<td>0.949 - 1.011</td>
</tr>
<tr>
<td>Japan</td>
<td>0.98</td>
<td>0.012</td>
<td>0.949 - 1.011</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.99</td>
<td>0.006</td>
<td>0.975 - 1.005</td>
</tr>
<tr>
<td>Norway</td>
<td>0.97</td>
<td>0.016</td>
<td>0.930 - 1.010</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.98</td>
<td>0.011</td>
<td>0.953 - 1.007</td>
</tr>
<tr>
<td>U.K.</td>
<td>0.96</td>
<td>0.023</td>
<td>0.900 - 1.020</td>
</tr>
<tr>
<td>U.S.</td>
<td>0.99</td>
<td>0.005</td>
<td>0.976 - 1.004</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Country</th>
<th>Correlation for 1975</th>
<th>Standard error s</th>
<th>Two-sided 99% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.92</td>
<td>0.068</td>
<td>0.745 - 1.095</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.95</td>
<td>0.030</td>
<td>0.872 - 1.028</td>
</tr>
<tr>
<td>Canada</td>
<td>0.96</td>
<td>0.022</td>
<td>0.902 - 1.018</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.88</td>
<td>0.058</td>
<td>0.730 - 1.030</td>
</tr>
<tr>
<td>Finland</td>
<td>0.89</td>
<td>0.054</td>
<td>0.751 - 1.029</td>
</tr>
<tr>
<td>France</td>
<td>0.97</td>
<td>0.018</td>
<td>0.923 - 1.017</td>
</tr>
<tr>
<td>Germany</td>
<td>0.97</td>
<td>0.016</td>
<td>0.928 - 1.012</td>
</tr>
<tr>
<td>Italy</td>
<td>0.96</td>
<td>0.023</td>
<td>0.900 - 1.020</td>
</tr>
<tr>
<td>Japan</td>
<td>0.93</td>
<td>0.040</td>
<td>0.828 - 1.032</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.98</td>
<td>0.011</td>
<td>0.951 - 1.009</td>
</tr>
<tr>
<td>Norway</td>
<td>0.85</td>
<td>0.071</td>
<td>0.667 - 1.033</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.94</td>
<td>0.031</td>
<td>0.861 - 1.019</td>
</tr>
<tr>
<td>U.K.</td>
<td>0.92</td>
<td>0.045</td>
<td>0.804 - 1.036</td>
</tr>
<tr>
<td>U.S.</td>
<td>0.99</td>
<td>0.005</td>
<td>0.976 - 1.004</td>
</tr>
</tbody>
</table>

(continued)
TABLE 3.3 (continued)

<table>
<thead>
<tr>
<th>Country</th>
<th>Correlation for 1970 $r^*$</th>
<th>Standard error $s^*$</th>
<th>Two-sided 99% confidence interval $r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.89</td>
<td>0.090</td>
<td>0.658 - 1.122</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.89</td>
<td>0.063</td>
<td>0.729 - 1.051</td>
</tr>
<tr>
<td>Canada</td>
<td>0.75</td>
<td>0.116</td>
<td>0.435 - 1.050</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.85</td>
<td>0.071</td>
<td>0.667 - 1.033</td>
</tr>
<tr>
<td>Finland</td>
<td>0.91</td>
<td>0.045</td>
<td>0.795 - 1.025</td>
</tr>
<tr>
<td>France</td>
<td>0.94</td>
<td>0.036</td>
<td>0.848 - 1.032</td>
</tr>
<tr>
<td>Germany</td>
<td>0.96</td>
<td>0.021</td>
<td>0.905 - 1.015</td>
</tr>
<tr>
<td>Italy</td>
<td>0.98</td>
<td>0.012</td>
<td>0.949 - 1.011</td>
</tr>
<tr>
<td>Japan</td>
<td>0.88</td>
<td>0.065</td>
<td>0.713 - 1.047</td>
</tr>
<tr>
<td>Netherlands</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Norway</td>
<td>0.82</td>
<td>0.083</td>
<td>0.606 - 1.034</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.91</td>
<td>0.045</td>
<td>0.795 - 1.025</td>
</tr>
<tr>
<td>U.K.</td>
<td>0.69</td>
<td>0.142</td>
<td>0.324 - 1.056</td>
</tr>
<tr>
<td>U.S.</td>
<td>0.97</td>
<td>0.016</td>
<td>0.930 - 1.010</td>
</tr>
</tbody>
</table>

* Source: Gittleman and Wolff (1993, p. 299, Table 2). For France and the Netherlands, correlations are with 1984.

* The numbers of sectors considered for the estimate of the Pearson correlation coefficients are: Australia (10), Belgium (16), Canada (18), Denmark (20), Finland (20), France (16), Germany (19), Italy (17), Japan (17), Netherlands (18), Norway (20), Sweden (20), U.K. (17), and U.S. (20).

* Calculated using equation (3.5), Sub-Section 3.2.1.

* Approximate two-sided 99% confidence intervals, under the assumption that $r$ follows an asymptotically normal distribution.

FIGURE 3.3

Gittleman and Wolff's industry wage differentials over time within countries:
Pearson correlation coefficients between 1985 and 1980 and two-sided 99% confidence intervals

![Graph showing Pearson correlation coefficients between 1985 and 1980 with 99% confidence intervals](image)
FIGURE 3.4
Gittleman and Wolff's industry wage differentials over time within countries:
Pearson correlation coefficients between 1985 and 1975 and two-sided 99% confidence intervals

FIGURE 3.5
Gittleman and Wolff's industry wage differentials over time within countries:
Pearson correlation coefficients between 1985 and 1970 and two-sided 99% confidence intervals
TABLE 3.4

Gittleman and Wolff's industry wage differentials over time within countries: estimated Pearson correlation coefficients with 1985 and confidence intervals based on t and z transformations, for all industries

<table>
<thead>
<tr>
<th>Country</th>
<th>Correlation for 1980</th>
<th>One-sided 99% confidence interval</th>
<th>One-sided 99.5% confidence interval</th>
<th>Fisher's z-transformation or r with Hotelling's correction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>r</td>
<td>t</td>
<td>z</td>
<td>t</td>
</tr>
<tr>
<td>Australia</td>
<td>0.95</td>
<td>0.732&lt;pt&lt;0.992</td>
<td>0.678&lt;pt&lt;0.993</td>
<td>1.768 0.369</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.99</td>
<td>0.964&lt;pt&lt;0.997</td>
<td>0.958&lt;pt&lt;0.998</td>
<td>2.610 0.274</td>
</tr>
<tr>
<td>Canada</td>
<td>0.98</td>
<td>0.934&lt;pt&lt;0.994</td>
<td>0.925&lt;pt&lt;0.995</td>
<td>2.266 0.255</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.96</td>
<td>0.880&lt;pt&lt;0.987</td>
<td>0.865&lt;pt&lt;0.989</td>
<td>1.918 0.240</td>
</tr>
<tr>
<td>Finland</td>
<td>0.98</td>
<td>0.939&lt;pt&lt;0.994</td>
<td>0.931&lt;pt&lt;0.994</td>
<td>2.720 0.240</td>
</tr>
<tr>
<td>France</td>
<td>0.99</td>
<td>0.964&lt;pt&lt;0.997</td>
<td>0.958&lt;pt&lt;0.998</td>
<td>2.610 0.274</td>
</tr>
<tr>
<td>Germany</td>
<td>0.99</td>
<td>0.968&lt;pt&lt;0.997</td>
<td>0.963&lt;pt&lt;0.997</td>
<td>2.617 0.247</td>
</tr>
<tr>
<td>Italy</td>
<td>0.98</td>
<td>0.931&lt;pt&lt;0.994</td>
<td>0.921&lt;pt&lt;0.995</td>
<td>2.264 0.264</td>
</tr>
<tr>
<td>Japan</td>
<td>0.98</td>
<td>0.931&lt;pt&lt;0.994</td>
<td>0.921&lt;pt&lt;0.995</td>
<td>2.264 0.264</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.99</td>
<td>0.967&lt;pt&lt;0.997</td>
<td>0.962&lt;pt&lt;0.997</td>
<td>2.615 0.255</td>
</tr>
<tr>
<td>Norway</td>
<td>0.97</td>
<td>0.909&lt;pt&lt;0.990</td>
<td>0.897&lt;pt&lt;0.991</td>
<td>2.065 0.240</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.98</td>
<td>0.939&lt;pt&lt;0.994</td>
<td>0.931&lt;pt&lt;0.994</td>
<td>2.270 0.240</td>
</tr>
<tr>
<td>U.K.</td>
<td>0.96</td>
<td>0.866&lt;pt&lt;0.998</td>
<td>0.847&lt;pt&lt;0.990</td>
<td>1.913 0.264</td>
</tr>
<tr>
<td>U.S.</td>
<td>0.99</td>
<td>0.969&lt;pt&lt;0.997</td>
<td>0.965&lt;pt&lt;0.997</td>
<td>2.618 0.240</td>
</tr>
</tbody>
</table>

(continued)
<table>
<thead>
<tr>
<th>Country</th>
<th>Correlation for 1975</th>
<th>One-sided 99% confidence interval</th>
<th>One-sided 99.5% confidence interval</th>
<th>Fisher's z-transformation of r with Hotelling's correction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$r'$</td>
<td>0.934&lt; $p$&lt;0.994</td>
<td>0.925&lt; $p$&lt;0.995</td>
<td>2.266 0.255 0.932&lt; $p$&lt;0.993 0.923&lt; $p$&lt;0.994</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.952&lt; $p$&lt;0.995</td>
<td>0.587&lt; $p$&lt;0.946</td>
<td>1.232 0.240 0.819&lt; $p$&lt;0.979 0.798&lt; $p$&lt;0.981</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.803&lt; $p$&lt;0.983</td>
<td>0.171 0.240 0.737&lt; $p$&lt;0.974</td>
<td>0.705&lt; $p$&lt;0.977</td>
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<tr>
<td></td>
<td></td>
<td>0.710&lt; $p$&lt;0.980</td>
<td>1.557 0.264 0.968&lt; $p$&lt;0.997</td>
<td>0.964&lt; $p$&lt;0.997</td>
</tr>
<tr>
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<td>0.744&lt; $p$&lt;0.977</td>
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<tr>
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<td></td>
<td>0.969&lt; $p$&lt;0.997</td>
<td>2.618 0.240 0.964&lt; $p$&lt;0.997</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Country</th>
<th>Correlation for 1970</th>
<th>One-sided 99% confidence interval</th>
<th>One-sided 99.5% confidence interval</th>
<th>Fisher's z-transformation of r with Hotelling's correction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$r'$</td>
<td>0.481&lt; $p$&lt;0.981</td>
<td>0.393&lt; $p$&lt;0.985</td>
<td>1.363 0.369 0.465&lt; $p$&lt;0.977 0.390&lt; $p$&lt;0.981</td>
</tr>
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<td></td>
<td></td>
<td>0.600&lt; $p$&lt;0.973</td>
<td>1.389 0.274 0.636&lt; $p$&lt;0.966</td>
<td>0.594&lt; $p$&lt;0.970</td>
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<tr>
<td></td>
<td></td>
<td>0.287&lt; $p$&lt;0.929</td>
<td>0.949 0.255 0.341&lt; $p$&lt;0.913</td>
<td>0.283&lt; $p$&lt;0.923</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.552&lt; $p$&lt;0.955</td>
<td>1.232 0.240 0.587&lt; $p$&lt;0.946</td>
<td>0.546&lt; $p$&lt;0.952</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.713&lt; $p$&lt;0.974</td>
<td>1.502 0.240 0.737&lt; $p$&lt;0.968</td>
<td>0.708&lt; $p$&lt;0.972</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.765&lt; $p$&lt;0.986</td>
<td>1.703 0.274 0.788&lt; $p$&lt;0.982</td>
<td>0.761&lt; $p$&lt;0.984</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.859&lt; $p$&lt;0.989</td>
<td>1.917 0.247 0.872&lt; $p$&lt;0.986</td>
<td>0.856&lt; $p$&lt;0.988</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.921&lt; $p$&lt;0.995</td>
<td>2.264 0.264 0.929&lt; $p$&lt;0.994</td>
<td>0.919&lt; $p$&lt;0.994</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.588&lt; $p$&lt;0.969</td>
<td>1.345 0.264 0.624&lt; $p$&lt;0.961</td>
<td>0.582&lt; $p$&lt;0.966</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.479&lt; $p$&lt;0.946</td>
<td>1.133 0.240 0.519&lt; $p$&lt;0.934</td>
<td>0.474&lt; $p$&lt;0.942</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.713&lt; $p$&lt;0.974</td>
<td>1.502 0.240 0.737&lt; $p$&lt;0.968</td>
<td>0.708&lt; $p$&lt;0.972</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.145&lt; $p$&lt;0.914</td>
<td>0.824 0.264 0.207&lt; $p$&lt;0.893</td>
<td>0.143&lt; $p$&lt;0.906</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.897&lt; $p$&lt;0.991</td>
<td>2.065 0.240 0.906&lt; $p$&lt;0.990</td>
<td>0.895&lt; $p$&lt;0.991</td>
</tr>
</tbody>
</table>

* Source: Gittleman and Wolff (1993, p.299, Table 2). For France and the Netherlands, correlations are with 1984.*

* The numbers of sectors considered for the estimate of the Pearson correlation coefficients are: Australia (10); Belgium (16); Canada (18); Denmark (20); Finland (20); France (16); Germany (19); Italy (17); Japan (17); Netherlands (18); Norway (20); Sweden (20); U.K. (17); and U.S. (20).*

* Confidence interval for the one-tail test of the null hypothesis $H_0: p = 0$ against the alternative $H_1: p > 0$ (positive correlation) at the 1% level, or for the one-tail test of the null hypothesis $H_0: p = 0$ against the alternative $H_1: p > 0$ (positive correlation) at the 1% level.*

* Confidence interval for the one-tail test of the null hypothesis $H_0: p = 0$ against the alternative $H_1: p > 0$ (positive correlation) at the 0.5% level, or for the one-tail test of the null hypothesis $H_0: p = 0$ against the alternative $H_1: p > 0$ (positive correlation) at the 0.5% level.
of a positive correlation as high as $p = 0.90$ against the alternative $p < 0.90$ cannot be rejected for almost any sample Pearson correlation between wage structures in all years and all countries, both at the 1% and at the 0.5% significance level. The only exception is for the U.K. in 1970, where the sample correlation $r = 0.69$ leads to the rejection of the null hypothesis $p = 0.90$ at the 1% significance level, but not at the 0.5% level. At the same time, the null hypothesis of total independence $p = 0$ against the alternative $p > 0$ can be rejected at the 1% and 0.5% significance level in all cases.

Although these results seem to point to the existence of a strong stability of industry wage structures over time in all countries, it is again worth taking into account the considerable width of many confidence intervals. Due to the small sample sizes, 99% confidence intervals for the correlations between 1985 and 1980 vary between (-0.02, +0.01) around $r = 0.99$ for the U.S. and (-0.23, +0.04) around $r = 0.95$ for Australia or, as percentages of the respective $r$, between (-2%, +1%) and (-24%, +4%). The average 99% confidence interval around $r$ is (-6%, +2%) of $r$. Intervals at the 99.5% confidence level are of course even wider. For the correlations between 1985 and 1975, 99% confidence intervals range from (-0.02, +0.01) around $r = 0.99$ for the U.S. to (-0.34, +0.06) around $r = 0.92$ for Australia, or in percentage points from (-2%, +1%) to (-37%, +7%). The average interval is (-16%, +5%) around $r$. Confidence intervals become wider and wider the further back in time one goes. For the correlations between 1985 and 1970, the 99% intervals vary between (-0.05, +0.01) around $r = 0.98$ for Italy and (-0.48, +0.20) around $r = 0.69$ for the U.K. or between (-5%, +1%) and (-70%, +29%) of $r$. The average confidence interval becomes (-29%, +10%). So Gittleman and Wolff’s sample evidence is in fact consistent with true population Pearson correlations like, for example, 0.72 (for Australia in 1980) or 0.59 (for Norway in 1975) or even as small as 0.21 (for the U.K. in 1970). And this kind of values of the population correlation can hardly be regarded as suggestive of a strong inter-temporal stability of industry wage differentials.

The results obtained by Gittleman and Wolff for Pearson correlations are essentially confirmed by their findings in terms of Spearman rank correlation coefficients and coefficients of concordance. As already mentioned in Sub-Sections 3.2.2 and 3.2.3, when these two metrics are considered one can only test the hypothesis of no association existing in the
underlying population, while it is not possible to evaluate in a statistically rigorous way whether the estimated coefficients are indicative of a strong positive relationship, as asserted by the authors. Table 3.5 reports the values of Spearman correlations between the 1985 industry wage structure and wage differentials in 1980, 1975, and 1970 for the 14 OECD countries. Again, correlations with 1985 tend to fall the further back in time one goes, but remain quite high for all countries. In 1980, all correlations but one - that for Australia - exceed 0.90; in 1975, 10 of the 14 countries present correlations greater than 0.90 and in the other 4 countries they range between 0.84 and 0.89; in 1970, 3 correlations still exceed 0.90 and 8 are greater than 0.80. Table 3.5 also provides the one-sided p-values for the tests of the null hypothesis $\rho_s = 0$ against the alternative hypothesis $\rho_s > 0$. Since the sample size for all countries is smaller than or equal to 20, I referred to Zar's table (Zar, 1972) for the critical values of $r_s$ for one-tailed probabilities. As we can see, the null hypothesis of no association is rejected in all cases at a very low significance level.

The results for the coefficient of concordance are given in Table 3.6, together with the outcomes for the tests of their statistical significance. Gittleman and Wolff compute, for all countries, the coefficient of concordance among industry wage differentials over the period 1970-85. With the exception of Canada and the U.K., all values are greater than 0.90. The tests of the null hypothesis $\omega = 0$ against the alternative $\omega > 0$ - based on the $F$-transformation of $W$ defined by equation (3.17) - indicate that the null hypothesis of no agreement in the population among wage rankings across years is rejected in all cases at an extremely low significance level. As previously observed (see Sub-Section 3.2.3), however, these tests are not especially meaningful. The significance of the coefficient of concordance is highly sensitive to the number of rankings compared (the number of years in the period considered, in the present context) and when this number is sufficiently large - for example, when $m = 16$ like in most of the cases here examined - even a coefficient of concordance as small as 0.20 is significantly greater than zero at the 1% level, for any sample size $n \geq 5$. It is nevertheless rather doubtful that a value of $W$ like 0.20 can be regarded as revealing a strong degree of stability among industry wage differentials.

To summarize all the previous findings, it seems that Krueger and Summers's and Gittleman and Wolff's assertion about the extreme stability of industry wage structures over
TABLE 3.5

Gittleman and Wolff's industry wage differentials over time within countries*: estimated Spearman correlation coefficients with 1985 and tests of their statistical significance, for all industries*

<table>
<thead>
<tr>
<th>Country</th>
<th>Rank correlation for 1980 $r^*$</th>
<th>One-sided p-value $^a$</th>
<th>Rank correlation for 1975 $r^*$</th>
<th>One-sided p-value $^a$</th>
<th>Rank correlation for 1970* $r^*$</th>
<th>One-sided p-value $^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.84</td>
<td>0.001&lt; $p&lt;$0.0025</td>
<td>0.84</td>
<td>0.001&lt; $p&lt;$0.0025</td>
<td>0.81</td>
<td>0.001&lt; $p&lt;$0.0025</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.99</td>
<td>$p&lt;$0.0005</td>
<td>0.92</td>
<td>$p&lt;$0.0005</td>
<td>0.82</td>
<td>$p&lt;$0.0005</td>
</tr>
<tr>
<td>Canada</td>
<td>0.96</td>
<td>$p&lt;$0.0005</td>
<td>0.97</td>
<td>$p&lt;$0.0005</td>
<td>0.74</td>
<td>$p&lt;$0.0005</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.94</td>
<td>$p&lt;$0.0005</td>
<td>0.88</td>
<td>$p&lt;$0.0005</td>
<td>0.85</td>
<td>$p&lt;$0.0005</td>
</tr>
<tr>
<td>Finland</td>
<td>0.99</td>
<td>$p&lt;$0.0005</td>
<td>0.84</td>
<td>$p&lt;$0.0005</td>
<td>0.88</td>
<td>$p&lt;$0.0005</td>
</tr>
<tr>
<td>France</td>
<td>0.91</td>
<td>$p&lt;$0.0005</td>
<td>0.93</td>
<td>$p&lt;$0.0005</td>
<td>0.88</td>
<td>$p&lt;$0.0005</td>
</tr>
<tr>
<td>Germany</td>
<td>0.98</td>
<td>$p&lt;$0.0005</td>
<td>0.96</td>
<td>$p&lt;$0.0005</td>
<td>0.94</td>
<td>$p&lt;$0.0005</td>
</tr>
<tr>
<td>Italy</td>
<td>0.98</td>
<td>$p&lt;$0.0005</td>
<td>0.96</td>
<td>$p&lt;$0.0005</td>
<td>0.96</td>
<td>$p&lt;$0.0005</td>
</tr>
<tr>
<td>Japan</td>
<td>0.96</td>
<td>$p&lt;$0.0005</td>
<td>0.93</td>
<td>$p&lt;$0.0005</td>
<td>0.89</td>
<td>$p&lt;$0.0005</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.98</td>
<td>$p&lt;$0.0005</td>
<td>0.92</td>
<td>$p&lt;$0.0005</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Norway</td>
<td>0.96</td>
<td>$p&lt;$0.0005</td>
<td>0.95</td>
<td>$p&lt;$0.0005</td>
<td>0.87</td>
<td>$p&lt;$0.0005</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.93</td>
<td>$p&lt;$0.0005</td>
<td>0.92</td>
<td>$p&lt;$0.0005</td>
<td>0.89</td>
<td>$p&lt;$0.0005</td>
</tr>
<tr>
<td>U.K.</td>
<td>0.93</td>
<td>$p&lt;$0.0005</td>
<td>0.89</td>
<td>$p&lt;$0.0005</td>
<td>0.66</td>
<td>0.0025&lt; $p&lt;$0.005</td>
</tr>
<tr>
<td>U.S.</td>
<td>0.97</td>
<td>$p&lt;$0.0005</td>
<td>0.97</td>
<td>$p&lt;$0.0005</td>
<td>0.97</td>
<td>$p&lt;$0.0005</td>
</tr>
</tbody>
</table>

$^*$ Source: Gittleman and Wolff (1993, p.299, Table 2). For France and the Netherlands, correlations are with 1984.

$^a$ The numbers of sectors considered for the estimate of the Spearman correlation coefficients are: Australia (10); Belgium (16); Canada (18); Denmark (20); Finland (20); France (16); Germany (19); Italy (17); Japan (17); Netherlands (18); Norway (20); Sweden (20); U.K. (17); and U.S. (20).

$^*$ One-sided $p$-values for the test of the null hypothesis $H_0: p = 0$, against the alternative hypothesis $H_1: p > 0$. See Zar (1972).
TABLE 3.6

Gittleman and Wolff’s industry wage differentials over time within countries*: estimated coefficients of concordance over the period 1970-85 and tests of their statistical significance, for all industries

<table>
<thead>
<tr>
<th>Country</th>
<th>Coefficient of concordance</th>
<th>Number of years</th>
<th>Number of sectors</th>
<th>F for $H_0: \omega = 0$</th>
<th>p-value$^*$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.93</td>
<td>16</td>
<td>10</td>
<td>199.286</td>
<td>0.00000</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.94</td>
<td>16</td>
<td>16</td>
<td>235.000</td>
<td>0.00000</td>
</tr>
<tr>
<td>Canada</td>
<td>0.86</td>
<td>16</td>
<td>18</td>
<td>92.143</td>
<td>0.00000</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.91</td>
<td>16</td>
<td>20</td>
<td>151.667</td>
<td>0.00000</td>
</tr>
<tr>
<td>Finland</td>
<td>0.92</td>
<td>16</td>
<td>20</td>
<td>172.500</td>
<td>0.00000</td>
</tr>
<tr>
<td>France</td>
<td>0.92</td>
<td>15</td>
<td>16</td>
<td>161.000</td>
<td>0.00000</td>
</tr>
<tr>
<td>Germany</td>
<td>0.98</td>
<td>16</td>
<td>19</td>
<td>735.000</td>
<td>0.00000</td>
</tr>
<tr>
<td>Italy</td>
<td>0.98</td>
<td>16</td>
<td>17</td>
<td>735.000</td>
<td>0.00000</td>
</tr>
<tr>
<td>Japan</td>
<td>0.96</td>
<td>16</td>
<td>17</td>
<td>360.000</td>
<td>0.00000</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.97</td>
<td>13</td>
<td>18</td>
<td>388.000</td>
<td>0.00000</td>
</tr>
<tr>
<td>Norway</td>
<td>0.96</td>
<td>16</td>
<td>20</td>
<td>360.000</td>
<td>0.00000</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.93</td>
<td>16</td>
<td>20</td>
<td>199.286</td>
<td>0.00000</td>
</tr>
<tr>
<td>U.K.</td>
<td>0.89</td>
<td>16</td>
<td>17</td>
<td>121.364</td>
<td>0.00000</td>
</tr>
<tr>
<td>U.S.</td>
<td>0.99</td>
<td>16</td>
<td>20</td>
<td>1485.000</td>
<td>0.00000</td>
</tr>
</tbody>
</table>

* Source: Gittleman and Wolff (1993, p.299, Table 2). For France, coefficient of concordance over the period 1970-84; for the Netherlands, coefficient of concordance over the period 1972-84.

$^*$ P-values for the one-tail test of the null hypothesis $H_0: \omega = 0$, against the alternative hypothesis $H_1: \omega > 0$. 
time is somewhat overstated. Firstly, the exact degree of association among industry wages in the underlying populations is quite difficult to evaluate. Empirical evidence from small samples consists of values of the sample measures of association which are compatible, in a statistical sense, with rather small values of the corresponding population measures in a large number of cases and, in some cases, even with no association at all in the population. Secondly, the conclusions drawn by Krueger and Summers and by Gittleman and Wolff are not totally in agreement. According to Krueger and Summers, the structure of U.S. industry wages remains essentially unchanged over a period of more than 60 years. And relying on some indirect evidence for other countries (Lawson, 1982; Papola and Bharadwaj, 1970; Tarling and Wilkinson, 1982), they generalize their result and conclude that "[...] stability in the industry wage structure is a universal phenomenon in industrialized capitalist countries." (Krueger and Summers, 1987, p.23). Such uniform patterns, they argue, seem to result "[...] from factors [...] which transcend the institutional setting in any particular time or place." (Krueger and Summers, 1987, p.17). Gittleman and Wolff show instead a clear tendency of industry wages in several countries to become less similar over a much shorter period of 15 years. Moreover, the speed of these changes varies across countries and this may well be consistent with differences in the institutional settings characterizing the various national labour markets, which also changed with different intensity over the period considered. These contrasting conclusions might be affected by differences in the wage variables employed, in the data sources and in the level of accuracy of industry classifications. They however cast some doubts on the overall reliability of this type of analysis of the inter-industry wage structure.

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16 These are Krueger and Summers's and Gittleman and Wolff's conclusions drawn from their own evidence. If attention is limited to the U.S. case over the period 1970-85, however, their Pearson correlations show in fact exactly the opposite phenomenon. Krueger and Summers's correlations between the 1984 U.S. industry wage structure and wage structures in 1980, 1975, and 1970 are 0.98, 0.96, and 0.91 respectively. Gittleman and Wolff find instead correlations between the U.S. industry wage differentials in 1985 and those in 1980, 1975, and 1970 equal to 0.99, 0.99, and 0.97. The authors' general conclusions can hence be justified only by considering a broader set of results: a longer time period in Krueger and Summers's case and a larger number of countries in Gittleman and Wolff's case.
3.4 Stability of Wage Structures across Countries

The second aspect considered by Krueger and Summers (1987) and by Gittleman and Wolff (1993) is the similarity of inter-industry wage structures across countries. Both analyses suggest as a general conclusion that the pattern of relative wages is remarkably similar among a large set of countries. Again, I will try to assess rigorously the statistical correctness of this statement. Similarly to the case of inter-temporal comparisons, small samples of industry wages are a typical feature in cross-country comparisons. Methods of industry classification differ across countries and so the larger the number of countries involved in the comparison, the less detailed the common industry classification and the smaller the size of samples of industry wages. Even in simple pair-wise comparisons, the need to define a common classification for the two countries usually leads to an increase in the level of aggregation of the industry classification. The trade-off between the number of countries considered and the number of industries retained in the common classification will appear clearly in the calculation of coefficients of concordance (Gittleman and Wolff, 1993), when several countries are compared simultaneously.

To evaluate the international stability of industry wages, Krueger and Summers (1987, pp.24-28) compare average wages of manufacturing industries in 1982 by computing Pearson correlation coefficients between various pairs of countries. The original data are drawn from the International Labour Office's Year Book of Labour Statistics (ILO, 1983). The variable considered is the logarithm of average manufacturing wages. The classification of manufacturing industries, the earnings measure and the type of workers covered by these data differ somehow across countries. Krueger and Summers describe in their data appendix the number of industries available for each country (Krueger and Summers, 1987, Table 2.A.1), but they do not specify the exact size of the samples actually used to compute Pearson correlations. In the analysis that follows, I assume the sample size to be equal, for each correlation, to the smaller of the two numbers of industry sectors available for the pair of countries involved in the correlation coefficient (see note b of Table 3.7). In the first part of Table 3.7, I present a sub-set of the results published by the authors, limiting my attention to 8 major industrialized Western countries. Krueger and Summers argue that these correlations show how the pattern of relative wages is remarkably similar across countries. Their values are regarded by them as quite high, ranging from 0.67 for the correlations...
TABLE 3.7

Krueger and Summers's industry wage structures across countries*: estimated Pearson correlation coefficients and confidence intervals based on t and z transformations, for log average manufacturing wages\(^a\), 1982

<table>
<thead>
<tr>
<th>Countries</th>
<th>Canada</th>
<th>France</th>
<th>Japan</th>
<th>U.S.</th>
<th>Germany</th>
<th>U.K.</th>
<th>Norway</th>
<th>Sweden</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td></td>
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<tr>
<td>Correlation</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Can,Fra</td>
<td>0.85</td>
<td>0.595 &lt;p &lt; 0.949</td>
<td>0.552 &lt;p &lt; 0.955</td>
<td>1.232</td>
<td>0.240</td>
<td>0.587 &lt;p &lt; 0.946</td>
<td>0.546 &lt;p &lt; 0.952</td>
<td></td>
</tr>
<tr>
<td>Can,Jap</td>
<td>0.82</td>
<td>0.539 &lt;p &lt; 0.937</td>
<td>0.493 &lt;p &lt; 0.944</td>
<td>1.135</td>
<td>0.234</td>
<td>0.531 &lt;p &lt; 0.933</td>
<td>0.488 &lt;p &lt; 0.940</td>
<td></td>
</tr>
<tr>
<td>Can,US</td>
<td>0.92</td>
<td>0.744 &lt;p &lt; 0.977</td>
<td>0.710 &lt;p &lt; 0.980</td>
<td>1.557</td>
<td>0.264</td>
<td>0.737 &lt;p &lt; 0.974</td>
<td>0.705 &lt;p &lt; 0.977</td>
<td></td>
</tr>
<tr>
<td>Can,Ger</td>
<td>0.83</td>
<td>0.561 &lt;p &lt; 0.940</td>
<td>0.517 &lt;p &lt; 0.947</td>
<td>1.166</td>
<td>0.234</td>
<td>0.553 &lt;p &lt; 0.937</td>
<td>0.511 &lt;p &lt; 0.943</td>
<td></td>
</tr>
<tr>
<td>Can,UK</td>
<td>0.88</td>
<td>0.876 &lt;p &lt; 0.959</td>
<td>0.641 &lt;p &lt; 0.963</td>
<td>1.352</td>
<td>0.234</td>
<td>0.669 &lt;p &lt; 0.956</td>
<td>0.635 &lt;p &lt; 0.961</td>
<td></td>
</tr>
<tr>
<td>Can,Nor</td>
<td>0.67</td>
<td>0.251 &lt;p &lt; 0.877</td>
<td>0.192 &lt;p &lt; 0.891</td>
<td>0.793</td>
<td>0.234</td>
<td>0.244 &lt;p &lt; 0.871</td>
<td>0.189 &lt;p &lt; 0.884</td>
<td></td>
</tr>
<tr>
<td>Can,Swe</td>
<td>0.79</td>
<td>0.476 &lt;p &lt; 0.925</td>
<td>0.426 &lt;p &lt; 0.934</td>
<td>1.050</td>
<td>0.234</td>
<td>0.467 &lt;p &lt; 0.921</td>
<td>0.421 &lt;p &lt; 0.929</td>
<td></td>
</tr>
<tr>
<td>Fra,Fra</td>
<td>0.95</td>
<td>0.852 &lt;p &lt; 0.984</td>
<td>0.833 &lt;p &lt; 0.986</td>
<td>1.805</td>
<td>0.240</td>
<td>0.847 &lt;p &lt; 0.982</td>
<td>0.829 &lt;p &lt; 0.984</td>
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</tr>
<tr>
<td>Fra,US</td>
<td>0.90</td>
<td>0.687 &lt;p &lt; 0.971</td>
<td>0.647 &lt;p &lt; 0.974</td>
<td>1.441</td>
<td>0.264</td>
<td>0.679 &lt;p &lt; 0.968</td>
<td>0.642 &lt;p &lt; 0.972</td>
<td></td>
</tr>
<tr>
<td>Fra,Ger</td>
<td>0.87</td>
<td>0.643 &lt;p &lt; 0.957</td>
<td>0.603 &lt;p &lt; 0.962</td>
<td>1.308</td>
<td>0.240</td>
<td>0.635 &lt;p &lt; 0.953</td>
<td>0.598 &lt;p &lt; 0.958</td>
<td></td>
</tr>
<tr>
<td>Fra,UK</td>
<td>0.93</td>
<td>0.796 &lt;p &lt; 0.977</td>
<td>0.771 &lt;p &lt; 0.980</td>
<td>1.632</td>
<td>0.240</td>
<td>0.791 &lt;p &lt; 0.975</td>
<td>0.767 &lt;p &lt; 0.978</td>
<td></td>
</tr>
<tr>
<td>Fra,Nor</td>
<td>0.80</td>
<td>0.484 &lt;p &lt; 0.931</td>
<td>0.433 &lt;p &lt; 0.939</td>
<td>1.076</td>
<td>0.240</td>
<td>0.475 &lt;p &lt; 0.927</td>
<td>0.428 &lt;p &lt; 0.935</td>
<td></td>
</tr>
<tr>
<td>Fra,Swe</td>
<td>0.84</td>
<td>0.572 &lt;p &lt; 0.946</td>
<td>0.527 &lt;p &lt; 0.952</td>
<td>1.197</td>
<td>0.240</td>
<td>0.564 &lt;p &lt; 0.942</td>
<td>0.522 &lt;p &lt; 0.948</td>
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<tr>
<td>Jap,US</td>
<td>0.89</td>
<td>0.660 &lt;p &lt; 0.967</td>
<td>0.617 &lt;p &lt; 0.972</td>
<td>1.391</td>
<td>0.264</td>
<td>0.651 &lt;p &lt; 0.964</td>
<td>0.611 &lt;p &lt; 0.969</td>
<td></td>
</tr>
<tr>
<td>Jap, Ger</td>
<td>0.86</td>
<td>0.629 &lt;p &lt; 0.951</td>
<td>0.589 &lt;p &lt; 0.957</td>
<td>1.270</td>
<td>0.234</td>
<td>0.621 &lt;p &lt; 0.948</td>
<td>0.584 &lt;p &lt; 0.954</td>
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(continued)
<table>
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<tr>
<th>Countries</th>
<th>Correlation ( r^* )</th>
<th>One-sided 99% confidence interval</th>
<th>One-sided 99.5% confidence interval</th>
<th>Fisher's ( z^* )</th>
<th>Fisher's ( z_1^* )</th>
<th>One-sided 99% confidence interval</th>
<th>One-sided 99.5% confidence interval</th>
</tr>
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<tbody>
<tr>
<td>Jap,UK</td>
<td>0.93</td>
<td>0.802&lt;( p &lt; 0.976 )</td>
<td>0.779&lt;( p &lt; 0.979 )</td>
<td>1.633</td>
<td>0.234</td>
<td>0.797&lt;( p &lt; 0.975 )</td>
<td>0.775&lt;( p &lt; 0.977 )</td>
</tr>
<tr>
<td>Jap,Nor</td>
<td>0.80</td>
<td>0.497&lt;( p &lt; 0.929 )</td>
<td>0.448&lt;( p &lt; 0.937 )</td>
<td>1.077</td>
<td>0.234</td>
<td>0.488&lt;( p &lt; 0.925 )</td>
<td>0.443&lt;( p &lt; 0.933 )</td>
</tr>
<tr>
<td>Jap,Swe</td>
<td>0.81</td>
<td>0.518&lt;( p &lt; 0.933 )</td>
<td>0.470&lt;( p &lt; 0.941 )</td>
<td>1.105</td>
<td>0.234</td>
<td>0.509&lt;( p &lt; 0.929 )</td>
<td>0.465&lt;( p &lt; 0.936 )</td>
</tr>
<tr>
<td>US,Ger</td>
<td>0.85</td>
<td>0.556&lt;( p &lt; 0.955 )</td>
<td>0.504&lt;( p &lt; 0.961 )</td>
<td>1.227</td>
<td>0.264</td>
<td>0.546&lt;( p &lt; 0.951 )</td>
<td>0.498&lt;( p &lt; 0.957 )</td>
</tr>
<tr>
<td>US,UK</td>
<td>0.95</td>
<td>0.834&lt;( p &lt; 0.986 )</td>
<td>0.811&lt;( p &lt; 0.987 )</td>
<td>1.799</td>
<td>0.264</td>
<td>0.829&lt;( p &lt; 0.984 )</td>
<td>0.807&lt;( p &lt; 0.986 )</td>
</tr>
<tr>
<td>US,Nor</td>
<td>0.67</td>
<td>0.179&lt;( p &lt; 0.894 )</td>
<td>0.108&lt;( p &lt; 0.907 )</td>
<td>0.788</td>
<td>0.264</td>
<td>0.172&lt;( p &lt; 0.886 )</td>
<td>0.107&lt;( p &lt; 0.899 )</td>
</tr>
<tr>
<td>US,Swe</td>
<td>0.82</td>
<td>0.483&lt;( p &lt; 0.945 )</td>
<td>0.426&lt;( p &lt; 0.953 )</td>
<td>1.129</td>
<td>0.264</td>
<td>0.473&lt;( p &lt; 0.941 )</td>
<td>0.420&lt;( p &lt; 0.948 )</td>
</tr>
<tr>
<td>Ger,UK</td>
<td>0.90</td>
<td>0.725&lt;( p &lt; 0.966 )</td>
<td>0.694&lt;( p &lt; 0.970 )</td>
<td>1.448</td>
<td>0.234</td>
<td>0.719&lt;( p &lt; 0.963 )</td>
<td>0.689&lt;( p &lt; 0.967 )</td>
</tr>
<tr>
<td>Ger,Nor</td>
<td>0.74</td>
<td>0.412&lt;( p &lt; 0.898 )</td>
<td>0.363&lt;( p &lt; 0.909 )</td>
<td>0.933</td>
<td>0.217</td>
<td>0.405&lt;( p &lt; 0.893 )</td>
<td>0.359&lt;( p &lt; 0.904 )</td>
</tr>
<tr>
<td>Ger,Swe</td>
<td>0.84</td>
<td>0.610&lt;( p &lt; 0.939 )</td>
<td>0.573&lt;( p &lt; 0.946 )</td>
<td>1.202</td>
<td>0.217</td>
<td>0.603&lt;( p &lt; 0.936 )</td>
<td>0.568&lt;( p &lt; 0.942 )</td>
</tr>
<tr>
<td>UK,Nor</td>
<td>0.70</td>
<td>0.304&lt;( p &lt; 0.890 )</td>
<td>0.246&lt;( p &lt; 0.902 )</td>
<td>0.848</td>
<td>0.234</td>
<td>0.296&lt;( p &lt; 0.884 )</td>
<td>0.242&lt;( p &lt; 0.896 )</td>
</tr>
<tr>
<td>UK,Swe</td>
<td>0.83</td>
<td>0.561&lt;( p &lt; 0.940 )</td>
<td>0.517&lt;( p &lt; 0.947 )</td>
<td>1.166</td>
<td>0.234</td>
<td>0.553&lt;( p &lt; 0.937 )</td>
<td>0.511&lt;( p &lt; 0.943 )</td>
</tr>
<tr>
<td>Nor,Swe</td>
<td>0.74</td>
<td>0.431&lt;( p &lt; 0.894 )</td>
<td>0.386&lt;( p &lt; 0.904 )</td>
<td>0.935</td>
<td>0.207</td>
<td>0.425&lt;( p &lt; 0.889 )</td>
<td>0.381&lt;( p &lt; 0.899 )</td>
</tr>
</tbody>
</table>

* Source: Krueger and Summers (1987, p.26, Table 2.3).

* For each country, average manufacturing wages are available for the following numbers of sectors (see Krueger and Summers, 1987, p.45, Table 2A1): Canada (21); France (20); Japan (21); U.S. (17); Germany (24); U.K. (21); Norway (27); and Sweden (26). For each pair of countries, the sample size for the estimate of the Pearson correlation coefficient is assumed to be:

<table>
<thead>
<tr>
<th>Countries</th>
<th>( n )</th>
<th>Countries</th>
<th>( n )</th>
<th>Countries</th>
<th>( n )</th>
<th>Countries</th>
<th>( n )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Can,Fra</td>
<td>20</td>
<td>Can,Swe</td>
<td>21</td>
<td>Fra,Swe</td>
<td>20</td>
<td>US,Ger</td>
<td>17</td>
</tr>
<tr>
<td>Can,Jap</td>
<td>21</td>
<td>Fra,Jap</td>
<td>20</td>
<td>Jap,US</td>
<td>17</td>
<td>US,UK</td>
<td>17</td>
</tr>
<tr>
<td>Can,US</td>
<td>17</td>
<td>Fra,US</td>
<td>17</td>
<td>Jap,US</td>
<td>17</td>
<td>US,Nor</td>
<td>17</td>
</tr>
<tr>
<td>Can,Ger</td>
<td>21</td>
<td>Fra,Ger</td>
<td>20</td>
<td>Jap,UK</td>
<td>21</td>
<td>US,Swe</td>
<td>17</td>
</tr>
<tr>
<td>Can,UK</td>
<td>21</td>
<td>Fra,UK</td>
<td>20</td>
<td>Jap,Nor</td>
<td>21</td>
<td>Ger,UK</td>
<td>21</td>
</tr>
<tr>
<td>Can,Nor</td>
<td>21</td>
<td>Fra,Nor</td>
<td>20</td>
<td>Jap,Swe</td>
<td>21</td>
<td>Ger,Nor</td>
<td>21</td>
</tr>
</tbody>
</table>

Data for international wage comparisons are derived from ILO (1983).

* Confidence interval for the one-tail test of the null hypothesis \( H_0: p = 0 \) against the alternative \( H_1: p > 0 \) (positive correlation) at the 1% level, or for the one-tail test of the null hypothesis \( H_0: p = p_0 \) against the alternative \( H_1: p < p_0 \) (large correlation) at the 1% level.

* Confidence interval for the one-tail test of the null hypothesis \( H_0: p = 0 \) against the alternative \( H_1: p > 0 \) (positive correlation) at the 0.5% level, or for the one-tail test of the null hypothesis \( H_0: p = p_0 \) against the alternative \( H_1: p < p_0 \) (large correlation) at the 0.5% level.
between Canada and Norway and between the U.S. and Norway to 0.95 for the correlations between France and Japan and between the U.S. and the U.K.. The authors suggest that such a regular pattern in the wage structure for diverse countries is evidence that some common aspects of labour markets, and not country specific institutions, are responsible for the observed industry wage differences (Krueger and Summers, 1987, p.37).

In order to evaluate accurately the statistical significance of the Pearson correlation coefficients appearing in Table 3.7, I construct hypothesis tests following the approaches previously described. Given the imprecision of interval estimation based on the assumption of asymptotic normality of \( r \) and on equation (3.5) for its standard error in small samples, already verified in Section 3.3, I will limit my attention to testing procedures based on the \( t \)- and \( z \)-transformations of the Pearson correlation coefficient \( r \). The results obtained for the one-sided 99% and 99.5% confidence intervals for \( p \) are reported in the second part of Table 3.7. Considering the \( z \)-transformation, which provides more accurate outcomes in the case of small samples, the null hypothesis of total independence \( p = 0 \) against the alternative \( p > 0 \) can be rejected in all cases, both at the 1% and at the 0.5% significance level. The null hypothesis of high positive correlation \( p = 0.90 \) against the alternative \( p < 0.90 \) is instead rejected for some of the sample correlations, namely for the correlations between Norway and Canada, the U.S., Germany, the U.K. and Sweden at the 1% significance level and for all these correlations but the one between Norway and Germany also at the 0.5% significance level.

Furthermore, all confidence intervals are considerably wide. The 99% intervals range from (-0.10, +0.03) around \( r = 0.95 \), for the correlation between France and Japan, to (-0.50, +0.22) around \( r = 0.67 \), for the correlation between the U.S. and Norway, or, as percentages of the respective \( r \), from (-11%, +3%) to (-74%, +32%). The average 99% confidence interval is (-33%, +13%) of \( r \). These results are certainly influenced by the small size of the samples involved and it must also be recalled that I have made a strong assumption about the size of the samples actually considered by Krueger and Summers for their correlation coefficients. This assumption is likely to lead to an overestimate of the real sample sizes, given the heterogeneity of the criteria used in different countries to classify industry sectors.
which may affect the degree of comparability\textsuperscript{17}. As I have already remarked, the smallness of the samples used to compute Pearson correlation coefficients may critically reduce their precision. For example, if a correlation of 0.67 - as in the case of the U.S. and Norway - were in fact computed with a sample of 13 pairs of observations, rather than the 17 I have assumed, it would not be significantly different from zero at the 0.5\% significance level\textsuperscript{18}.

The analysis of the international stability of industry wage structures proposed by Gittleman and Wolff (1993, pp.302-305) contemplates only comparisons between the U.S. and the other 13 OECD countries considered, but it is repeated over the period 1970-85 in order to verify whether the degree of similarity among countries changes through time. The data source and the wage variable utilized are the same illustrated in Section 3.3. The authors examine samples of average industry wages for manufacturing sectors only and for all industries. I will present and discuss both types of results. Evidence for manufacturing wage differentials is directly comparable with the findings of Krueger and Summers (1987). Evidence for all industries in the economy offers the possibility to evaluate the degree of similarity among countries in a broader and more informative sense. As observed by Krueger and Summers (1987), data on manufacturing wages refer only to a relatively small and shrinking part of the economy in developed countries. For example, in 1985, less than 20 percent of the U.S. labour force was working in the manufacturing sectors. One of the often claimed regularities in the industry wage structure is the tendency for manufacturing firms to pay high wages generally, while service sector firms tend to pay relatively low wages. For this reason, it is useful even at the cost of some sacrifice in data quality to examine information on the economy-wide wage structure. The exact number of sectors included in the various samples are reported in each of the Tables presented. For cross-country comparisons of industry wage differentials, Gittleman and Wolff calculate Pearson correlation coefficients between pairs of countries and coefficients of concordance among various sets of countries. The authors assert that both metrics provide evidence that the wage structures in the samples considered are remarkably similar and remain so over time (Gittleman and Wolff, 1993, p.304).

\textsuperscript{17} It seems, for example, that Krueger and Summers (see their Figure 2.2 on p.27, 1987) used a sample of only 13 pairs of observations - instead of the 17 theoretically available - for the correlation between log average manufacturing wages in the U.S. and Japan.

\textsuperscript{18} Test based on the \textit{z}-transformation.
The first two columns of Table 3.8 give the estimated Pearson correlations for the samples including all industries. Gittleman and Wolff calculate the correlations between the wage structures of 13 countries and that of the U.S. in 1985, 1980, 1975, and 1970. Correlation coefficients are regarded by the authors as quite high in all years. In 1970, they range from 0.59 to 0.90; in 1975, they range from 0.66 to 0.92; in 1980, they range from 0.67 to 0.91; and in 1985, they range from 0.65 to 0.93. However, the countries with the lowest and the highest degree of similarity with the U.S. are different in different years and no clear pattern emerges for changes in similarity over time. Some countries steadily become more similar to the U.S., others become less similar, and still others fluctuate (Gittleman and Wolff, 1993, p.304).

Table 3.8 also shows the outcomes for the 99% and 99.5% confidence intervals for \( \rho \) based on the \( t \)- and \( z \)-transformations of the Pearson correlation \( r \). Examining the results from the more accurate \( z \)-transformation, the null hypothesis of a high positive correlation \( \rho = 0.90 \) against the alternative \( \rho < 0.90 \) is rejected, in 1970, for Canada and Japan both at the 1% and at the 0.5% significance level and for Denmark and the U.K. only at the 1% level; in 1975, it is rejected for Finland, Italy and Japan at the 1% significance level; in 1980, it is rejected for Japan both at the 1% and at the 0.5% significance level and for Finland only at the 1% level; in 1985, it is rejected for Japan both at the 1% and at the 0.5% significance level. The null hypothesis of total independence \( \rho = 0 \) against the alternative \( \rho > 0 \) can be rejected in all cases, with the exception of the correlation between the U.S. and Australia in 1970, 1975 and 1980, both at the 1% and at the 0.5% significance level. Australia seems therefore the country with the lowest degree of similarity with the U.S., but this result is undoubtedly influenced by the fact that the comparison between Australia and the U.S. relies on the smallest sample (10 observations) and this produces the largest sampling error (see the column for \( s^2 \)).

Evidence from generally small samples is again characterized by very wide confidence intervals, which remain so over time. In 1970, 99% confidence intervals range from (-0.19, +0.06) for Norway to (-0.81, +0.31) for Australia or from (-21%, +7%) to (-137%, +53%) of 19 As it will be shown in the following Chapters, this result is contradicted by empirical evidence based on micro data.
TABLE 3.8

Gittleman and Wolff's industry wage structure across countries*; estimated Pearson correlation coefficients with U.S. industry wage differentials and confidence intervals based on $t$ and $z$ transformations, for all industries$^b$

<table>
<thead>
<tr>
<th>Country</th>
<th>Correlation for 1970 $r^*$</th>
<th>One-sided 99% confidence interval $t$</th>
<th>One-sided 99.5% confidence interval $t$</th>
<th>Fisher's $z$-transformation of $r$</th>
<th>One-sided 99% confidence interval $z$</th>
<th>One-sided 99.5% confidence interval $z$</th>
<th>One-sided 99% confidence interval $t$ with Hotelling's correction</th>
<th>One-sided 99.5% confidence interval $t$ with Hotelling's correction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.59</td>
<td>$-0.217&lt; p&lt;0.918$</td>
<td>$-0.318&lt; p&lt;0.933$</td>
<td>0.638</td>
<td>0.369</td>
<td>0.217&lt; $p&lt;0.905$</td>
<td>$-0.303&lt; p&lt;0.920$</td>
<td></td>
</tr>
<tr>
<td>Belgium</td>
<td>0.81</td>
<td>$0.441&lt; p&lt;0.945$</td>
<td>$0.378&lt; p&lt;0.952$</td>
<td>1.097</td>
<td>0.274</td>
<td>0.430&lt; $p&lt;0.940$</td>
<td>0.373&lt; $p&lt;0.947$</td>
<td></td>
</tr>
<tr>
<td>Canada</td>
<td>0.66</td>
<td>$0.183&lt; p&lt;0.885$</td>
<td>$0.115&lt; p&lt;0.900$</td>
<td>0.772</td>
<td>0.255</td>
<td>0.176&lt; $p&lt;0.878$</td>
<td>0.113&lt; $p&lt;0.892$</td>
<td></td>
</tr>
<tr>
<td>Denmark</td>
<td>0.73</td>
<td>$0.344&lt; p&lt;0.905$</td>
<td>$0.286&lt; p&lt;0.916$</td>
<td>0.908</td>
<td>0.240</td>
<td>0.336&lt; $p&lt;0.899$</td>
<td>0.281&lt; $p&lt;0.910$</td>
<td></td>
</tr>
<tr>
<td>Finland</td>
<td>0.82</td>
<td>$0.528&lt; p&lt;0.939$</td>
<td>$0.479&lt; p&lt;0.946$</td>
<td>1.133</td>
<td>0.240</td>
<td>0.519&lt; $p&lt;0.934$</td>
<td>0.474&lt; $p&lt;0.942$</td>
<td></td>
</tr>
<tr>
<td>France</td>
<td>0.90</td>
<td>$0.674&lt; p&lt;0.972$</td>
<td>$0.631&lt; p&lt;0.976$</td>
<td>1.439</td>
<td>0.274</td>
<td>0.665&lt; $p&lt;0.969$</td>
<td>0.625&lt; $p&lt;0.973$</td>
<td></td>
</tr>
<tr>
<td>Germany</td>
<td>0.82</td>
<td>$0.514&lt; p&lt;0.941$</td>
<td>$0.464&lt; p&lt;0.948$</td>
<td>1.322</td>
<td>0.247</td>
<td>0.505&lt; $p&lt;0.936$</td>
<td>0.458&lt; $p&lt;0.944$</td>
<td></td>
</tr>
<tr>
<td>Italy</td>
<td>0.71</td>
<td>$0.252&lt; p&lt;0.908$</td>
<td>$0.183&lt; p&lt;0.920$</td>
<td>0.863</td>
<td>0.264</td>
<td>0.243&lt; $p&lt;0.901$</td>
<td>0.180&lt; $p&lt;0.913$</td>
<td></td>
</tr>
<tr>
<td>Japan</td>
<td>0.63</td>
<td>$0.112&lt; p&lt;0.879$</td>
<td>$0.040&lt; p&lt;0.894$</td>
<td>0.720</td>
<td>0.264</td>
<td>0.105&lt; $p&lt;0.870$</td>
<td>0.039&lt; $p&lt;0.885$</td>
<td></td>
</tr>
<tr>
<td>Netherlands$^c$</td>
<td>0.84</td>
<td>$0.547&lt; p&lt;0.950$</td>
<td>$0.496&lt; p&lt;0.956$</td>
<td>1.194</td>
<td>0.255</td>
<td>0.537&lt; $p&lt;0.946$</td>
<td>0.490&lt; $p&lt;0.952$</td>
<td></td>
</tr>
<tr>
<td>Norway</td>
<td>0.90</td>
<td>$0.717&lt; p&lt;0.967$</td>
<td>$0.684&lt; p&lt;0.971$</td>
<td>1.447</td>
<td>0.240</td>
<td>0.710&lt; $p&lt;0.964$</td>
<td>0.679&lt; $p&lt;0.968$</td>
<td></td>
</tr>
<tr>
<td>Sweden</td>
<td>0.77</td>
<td>$0.422&lt; p&lt;0.920$</td>
<td>$0.367&lt; p&lt;0.930$</td>
<td>0.998</td>
<td>0.240</td>
<td>0.413&lt; $p&lt;0.915$</td>
<td>0.362&lt; $p&lt;0.924$</td>
<td></td>
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<tr>
<td>U.K.</td>
<td>0.69</td>
<td>$0.215&lt; p&lt;0.901$</td>
<td>$0.145&lt; p&lt;0.914$</td>
<td>0.824</td>
<td>0.264</td>
<td>0.207&lt; $p&lt;0.893$</td>
<td>0.143&lt; $p&lt;0.906$</td>
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</table>

(continued)
<table>
<thead>
<tr>
<th>Country</th>
<th>Correlation for 1980</th>
<th>Sammulin’s t-transformation of r</th>
<th>Fisher’s z-transformation of r with Hotelling’s correction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$r^*$</td>
<td>One-sided 99% confidence interval $t_1$</td>
<td>One-sided 99.5% confidence interval $t_2$</td>
</tr>
<tr>
<td>Australia</td>
<td>0.70</td>
<td>-0.031&lt;p&lt;0.943</td>
<td>-0.139&lt;p&lt;0.954</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.82</td>
<td>0.465&lt;p&lt;0.948</td>
<td>0.403&lt;p&lt;0.955</td>
</tr>
<tr>
<td>Canada</td>
<td>0.78</td>
<td>0.412&lt;p&lt;0.929</td>
<td>0.352&lt;p&lt;0.938</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.77</td>
<td>0.422&lt;p&lt;0.920</td>
<td>0.367&lt;p&lt;0.930</td>
</tr>
<tr>
<td>Finland</td>
<td>0.72</td>
<td>0.325&lt;p&lt;0.901</td>
<td>0.266&lt;p&lt;0.913</td>
</tr>
<tr>
<td>France</td>
<td>0.84</td>
<td>0.513&lt;p&lt;0.954</td>
<td>0.456&lt;p&lt;0.960</td>
</tr>
<tr>
<td>Germany</td>
<td>0.82</td>
<td>0.514&lt;p&lt;0.941</td>
<td>0.464&lt;p&lt;0.948</td>
</tr>
<tr>
<td>Italy</td>
<td>0.73</td>
<td>0.291&lt;p&lt;0.915</td>
<td>0.223&lt;p&lt;0.926</td>
</tr>
<tr>
<td>Japan</td>
<td>0.67</td>
<td>0.179&lt;p&lt;0.894</td>
<td>0.108&lt;p&lt;0.907</td>
</tr>
<tr>
<td>Netherlands*</td>
<td>0.81</td>
<td>0.477&lt;p&lt;0.940</td>
<td>0.422&lt;p&lt;0.947</td>
</tr>
<tr>
<td>Norway</td>
<td>0.80</td>
<td>0.484&lt;p&lt;0.931</td>
<td>0.433&lt;p&lt;0.939</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.77</td>
<td>0.422&lt;p&lt;0.920</td>
<td>0.367&lt;p&lt;0.930</td>
</tr>
<tr>
<td>U.K.</td>
<td>0.91</td>
<td>0.715&lt;p&lt;0.974</td>
<td>0.678&lt;p&lt;0.977</td>
</tr>
</tbody>
</table>

| Country       | Correlation for 1985 | One-sided 99% confidence interval $t_1$ | One-sided 99.5% confidence interval $t_2$ | $z^*$ | $z_{1.0}$ | One-sided 99% confidence interval $z_1$ | One-sided 99.5% confidence interval $z_2$ |
|---------------|----------------------|----------------------------------|----------------------------------------------------------|
| Australia     | 0.82                 | 0.253<p<0.968                   | 0.149<p<0.974                                       | 1.102 | 0.369 | 0.239<p<0.961                             | 0.150<p<0.968                             |
| Belgium       | 0.90                 | 0.674<p<0.972                   | 0.631<p<0.976                                       | 1.439 | 0.274 | 0.665<p<0.969                             | 0.625<p<0.973                             |
| Canada        | 0.82                 | 0.500<p<0.943                   | 0.446<p<0.950                                       | 1.130 | 0.255 | 0.490<p<0.938                             | 0.440<p<0.946                             |
| Denmark       | 0.76                 | 0.402<p<0.916                   | 0.346<p<0.926                                       | 0.975 | 0.240 | 0.393<p<0.911                             | 0.341<p<0.921                             |
| Finland       | 0.76                 | 0.402<p<0.916                   | 0.346<p<0.926                                       | 0.975 | 0.240 | 0.393<p<0.911                             | 0.341<p<0.921                             |
| France        | 0.81                 | 0.441<p<0.945                   | 0.378<p<0.952                                       | 1.097 | 0.274 | 0.430<p<0.940                             | 0.373<p<0.947                             |
| Germany       | 0.86                 | 0.608<p<0.955                   | 0.564<p<0.960                                       | 1.267 | 0.247 | 0.599<p<0.951                             | 0.558<p<0.957                             |
| Italy         | 0.78                 | 0.393<p<0.932                   | 0.331<p<0.941                                       | 1.018 | 0.264 | 0.383<p<0.926                             | 0.326<p<0.935                             |
| Japan         | 0.65                 | 0.145<p<0.886                   | 0.073<p<0.901                                       | 0.753 | 0.264 | 0.138<p<0.878                             | 0.072<p<0.892                             |
| Netherlands*  | 0.86                 | 0.595<p<0.956                   | 0.548<p<0.962                                       | 1.266 | 0.255 | 0.586<p<0.953                             | 0.543<p<0.958                             |
| Norway        | 0.78                 | 0.442<p<0.924                   | 0.389<p<0.933                                       | 1.023 | 0.240 | 0.434<p<0.919                             | 0.384<p<0.928                             |
| Sweden        | 0.78                 | 0.442<p<0.924                   | 0.389<p<0.933                                       | 1.023 | 0.240 | 0.434<p<0.919                             | 0.384<p<0.928                             |
| U.K.          | 0.93                 | 0.773<p<0.980                   | 0.743<p<0.982                                       | 1.626 | 0.264 | 0.767<p<0.978                             | 0.738<p<0.980                             |


* The number of sectors included for each pair-wise Pearson correlation with the U.S. is as follows: Australia (10); Belgium (16); Canada (18); Denmark (20); Finland (20); France (16); Germany (19); Italy (17); Japan (17); Netherlands (18); Norway (20); Sweden (20); and U.K. (17).

* Confidence interval for the one-tail test of the null hypothesis $H_0$: $p = 0$ against the alternative $H_A$: $p > 0$ (positive correlation) at the 1% level, or for the one tail test of the null hypothesis $H_0$: $p = 0$ against the alternative $H_A$: $p < 0$ (large correlation) at the 1% level.

* Confidence interval for the one-tail test of the null hypothesis $H_0$: $p = 0$ against the alternative $H_A$: $p > 0$ (positive correlation) at the 5% level, or for the one tail test of the null hypothesis $H_0$: $p = 0$ against the alternative $H_A$: $p < 0$ (large correlation) at the 5% level.

* The employment concept used to calculate average wages is total employment instead of number of employees.
the respective $r$, with an average interval of (-57%, +23%); in 1975, they range from (-0.18, +0.05) for the U.K. to (-0.77, +0.26) for Australia or from (-20%, +6%) to (-117%, +40%). with an average interval of (-51%, +19%); in 1980, they range from (-0.20, +0.06) for the U.K. to (-0.74, +0.23) for Australia or from (-22%, +7%) to (-105%, +33%), with an average interval of (-51%, +19%); in 1985, they range from (-0.16, +0.05) for the U.K. to (-0.51, +0.23) for Japan or from (-18%, +5%) to (-79%, +35%), with an average interval of (-45%, +16%). So, again, Gittleman and Wolff's sample evidence is statistically consistent with broad ranges of plausible values for the true population correlations and several of these values are so small that they would seriously affect the conclusions drawn about the degree of similarity of industry wage differentials across countries.

The Pearson correlations estimated by Gittleman and Wolff with samples including only manufacturing industries are reported in Table 3.9. As in the previous case, correlations between the U.S. and the other countries are calculated for 1985, 1980, 1975, and 1970. As expected, correlation coefficients tend to be higher than in the case in which all industries are considered, still a clear tendency for changes in similarity over time does not emerge. In all years, sample correlations equal or exceed 0.90 for a large number of countries. However, the size of the samples here examined is much smaller than that of the samples including all industries and this is likely to affect the statistical significance even of high correlations. Tests of the null hypotheses of total independence and of high positive dependence are conducted again through confidence intervals based on the $t$- and $z$-transformations of the Pearson correlation $r$. While the null hypothesis of a positive correlation as high as $\rho = 0.90$ against the alternative $\rho < 0.90$ cannot be rejected in any case, the null hypothesis of total independence $\rho = 0$ against the alternative $\rho > 0$ cannot be rejected for some of the sample correlations: in 1970, for Canada both at the 1% and at the 0.5% significance level and for Sweden only at the 0.5% level; in 1975, for France and Sweden at the 0.5% significance level; in 1980, for Belgium and France at the 0.5% significance level; in 1985, for France, Japan and Sweden both at the 1% and at the 0.5% significance level. Confidence intervals for $\rho$ are again considerably wide. Looking at the outcomes for the more accurate $z$-transformation in 1970, 99% confidence intervals range from (-0.27, +0.03) for Belgium to (-0.88, +0.35) for Canada or from (-28%, +3%) to (-158%, +62%) of the respective $r$, with an average interval of (-59%, +13%); in 1975, they range from (-0.27, +0.04) for Norway to (-0.76,
### TABLE 3.9

Gittleman and Wolff's industry wage structure across countries*: estimated Pearson correlation coefficients with U.S. industry wage differentials and confidence intervals based on t and z transformations, for manufacturing industries.

<table>
<thead>
<tr>
<th>Country</th>
<th>Correlation for 1970</th>
<th>Summaddin's ½ transformation of r</th>
<th>Fisher's ½ transformation of r with Hotelling's correction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>One-sided 99% confidence interval</td>
<td>One-sided 99.5% confidence interval</td>
</tr>
<tr>
<td>Australia</td>
<td>0.96</td>
<td>0.705$p&lt;0.995$</td>
<td>0.631$p&lt;0.996$</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.56</td>
<td>-0.327$p&lt;0.922$</td>
<td>-0.429$p&lt;0.938$</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.90</td>
<td>0.462$p&lt;0.985$</td>
<td>0.363$p&lt;0.988$</td>
</tr>
<tr>
<td>Finland</td>
<td>0.95</td>
<td>0.696$p&lt;0.993$</td>
<td>0.629$p&lt;0.994$</td>
</tr>
<tr>
<td>France</td>
<td>0.92</td>
<td>0.478$p&lt;0.990$</td>
<td>0.369$p&lt;0.993$</td>
</tr>
<tr>
<td>Germany</td>
<td>0.93</td>
<td>0.595$p&lt;0.990$</td>
<td>0.513$p&lt;0.992$</td>
</tr>
<tr>
<td>Italy</td>
<td>0.93</td>
<td>0.595$p&lt;0.990$</td>
<td>0.513$p&lt;0.992$</td>
</tr>
<tr>
<td>Japan</td>
<td>0.86</td>
<td>0.221$p&lt;0.982$</td>
<td>0.091$p&lt;0.986$</td>
</tr>
<tr>
<td>Netherlands*</td>
<td>0.91</td>
<td>0.430$p&lt;0.989$</td>
<td>0.314$p&lt;0.992$</td>
</tr>
<tr>
<td>Norway</td>
<td>0.92</td>
<td>0.549$p&lt;0.988$</td>
<td>0.460$p&lt;0.991$</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.79</td>
<td>0.099$p&lt;0.967$</td>
<td>-0.021$p&lt;0.974$</td>
</tr>
<tr>
<td>U.K.</td>
<td>0.91</td>
<td>0.430$p&lt;0.989$</td>
<td>0.314$p&lt;0.992$</td>
</tr>
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</table>

* (continued)
<table>
<thead>
<tr>
<th>Country</th>
<th>Correlation for 1980</th>
<th>One-sided 99% confidence interval</th>
<th>One-sided 99.5% confidence interval</th>
<th>Fisher's z-transformation of r with Hotelling's correction</th>
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<tbody>
<tr>
<td></td>
<td>r*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Australia</td>
<td>0.83</td>
<td>0.199 &lt; p &lt; 0.978</td>
<td>-0.014 &lt; p &lt; 0.983</td>
<td>1.13 0.433 1.05 &lt; p &lt; 0.972 -0.003 &lt; p &lt; 0.977</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.93</td>
<td>0.595 &lt; p &lt; 0.990</td>
<td>0.513 &lt; p &lt; 0.992</td>
<td>1.587 0.397 0.580 &lt; p &lt; 0.987 0.510 &lt; p &lt; 0.989</td>
</tr>
<tr>
<td>Canada</td>
<td>0.80</td>
<td>0.125 &lt; p &lt; 0.969</td>
<td>0.007 &lt; p &lt; 0.975</td>
<td>1.037 0.397 0.112 &lt; p &lt; 0.961 0.013 &lt; p &lt; 0.968</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.91</td>
<td>0.504 &lt; p &lt; 0.987</td>
<td>0.410 &lt; p &lt; 0.989</td>
<td>1.458 0.397 0.488 &lt; p &lt; 0.983 0.409 &lt; p &lt; 0.986</td>
</tr>
<tr>
<td>Finland</td>
<td>0.82</td>
<td>0.088 &lt; p &lt; 0.977</td>
<td>-0.045 &lt; p &lt; 0.982</td>
<td>1.082 0.433 0.075 &lt; p &lt; 0.970 -0.033 &lt; p &lt; 0.976</td>
</tr>
<tr>
<td>France</td>
<td>0.89</td>
<td>0.421 &lt; p &lt; 0.983</td>
<td>0.318 &lt; p &lt; 0.987</td>
<td>1.353 0.397 0.405 &lt; p &lt; 0.979 0.318 &lt; p &lt; 0.983</td>
</tr>
<tr>
<td>Germany</td>
<td>0.89</td>
<td>0.421 &lt; p &lt; 0.983</td>
<td>0.318 &lt; p &lt; 0.987</td>
<td>1.353 0.397 0.405 &lt; p &lt; 0.979 0.318 &lt; p &lt; 0.983</td>
</tr>
<tr>
<td>Italy</td>
<td>0.86</td>
<td>0.221 &lt; p &lt; 0.982</td>
<td>0.091 &lt; p &lt; 0.986</td>
<td>1.215 0.433 0.205 &lt; p &lt; 0.977 0.099 &lt; p &lt; 0.981</td>
</tr>
<tr>
<td>Japan</td>
<td>0.92</td>
<td>0.478 &lt; p &lt; 0.990</td>
<td>0.369 &lt; p &lt; 0.993</td>
<td>1.505 0.433 0.461 &lt; p &lt; 0.987 0.371 &lt; p &lt; 0.989</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.96</td>
<td>0.750 &lt; p &lt; 0.994</td>
<td>0.693 &lt; p &lt; 0.995</td>
<td>1.872 0.397 0.739 &lt; p &lt; 0.993 0.690 &lt; p &lt; 0.994</td>
</tr>
<tr>
<td>Norway</td>
<td>0.80</td>
<td>0.125 &lt; p &lt; 0.969</td>
<td>0.007 &lt; p &lt; 0.975</td>
<td>1.037 0.397 0.112 &lt; p &lt; 0.961 0.013 &lt; p &lt; 0.968</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.88</td>
<td>0.298 &lt; p &lt; 0.985</td>
<td>0.172 &lt; p &lt; 0.989</td>
<td>1.296 0.433 0.281 &lt; p &lt; 0.980 0.178 &lt; p &lt; 0.984</td>
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<table>
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<th>Country</th>
<th>Correlation for 1985</th>
<th>One-sided 99% confidence interval</th>
<th>One-sided 99.5% confidence interval</th>
<th>Fisher's z-transformation of r with Hotelling's correction</th>
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<tbody>
<tr>
<td></td>
<td>r*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Australia</td>
<td>0.89</td>
<td>0.340 &lt; p &lt; 0.986</td>
<td>0.216 &lt; p &lt; 0.990</td>
<td>1.341 0.433 0.322 &lt; p &lt; 0.982 0.222 &lt; p &lt; 0.985</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.93</td>
<td>0.595 &lt; p &lt; 0.990</td>
<td>0.513 &lt; p &lt; 0.992</td>
<td>1.587 0.397 0.580 &lt; p &lt; 0.987 0.510 &lt; p &lt; 0.989</td>
</tr>
<tr>
<td>Canada</td>
<td>0.82</td>
<td>0.182 &lt; p &lt; 0.972</td>
<td>0.065 &lt; p &lt; 0.978</td>
<td>1.094 0.397 0.168 &lt; p &lt; 0.965 0.070 &lt; p &lt; 0.971</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.91</td>
<td>0.504 &lt; p &lt; 0.987</td>
<td>0.410 &lt; p &lt; 0.989</td>
<td>1.458 0.397 0.488 &lt; p &lt; 0.983 0.409 &lt; p &lt; 0.986</td>
</tr>
<tr>
<td>Finland</td>
<td>0.78</td>
<td>-0.023 &lt; p &lt; 0.971</td>
<td>-0.156 &lt; p &lt; 0.976</td>
<td>0.974 0.433 -0.033 &lt; p &lt; 0.963 -0.140 &lt; p &lt; 0.970</td>
</tr>
<tr>
<td>Germany</td>
<td>0.89</td>
<td>0.421 &lt; p &lt; 0.983</td>
<td>0.318 &lt; p &lt; 0.987</td>
<td>1.353 0.397 0.405 &lt; p &lt; 0.979 0.318 &lt; p &lt; 0.983</td>
</tr>
<tr>
<td>Italy</td>
<td>0.88</td>
<td>0.383 &lt; p &lt; 0.982</td>
<td>0.276 &lt; p &lt; 0.986</td>
<td>1.308 0.397 0.366 &lt; p &lt; 0.977 0.277 &lt; p &lt; 0.981</td>
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<tr>
<td>Japan</td>
<td>0.73</td>
<td>-0.138 &lt; p &lt; 0.964</td>
<td>-0.267 &lt; p &lt; 0.972</td>
<td>0.862 0.433 -0.144 &lt; p &lt; 0.954 -0.248 &lt; p &lt; 0.962</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.94</td>
<td>0.585 &lt; p &lt; 0.993</td>
<td>0.490 &lt; p &lt; 0.994</td>
<td>1.653 0.433 0.569 &lt; p &lt; 0.990 0.491 &lt; p &lt; 0.992</td>
</tr>
<tr>
<td>Norway</td>
<td>0.96</td>
<td>0.750 &lt; p &lt; 0.994</td>
<td>0.693 &lt; p &lt; 0.995</td>
<td>1.872 0.397 0.739 &lt; p &lt; 0.993 0.690 &lt; p &lt; 0.994</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.74</td>
<td>-0.022 &lt; p &lt; 0.958</td>
<td>-0.141 &lt; p &lt; 0.967</td>
<td>0.894 0.397 -0.013 &lt; p &lt; 0.949 -0.129 &lt; p &lt; 0.958</td>
</tr>
<tr>
<td>U.K.</td>
<td>0.89</td>
<td>0.340 &lt; p &lt; 0.986</td>
<td>0.216 &lt; p &lt; 0.990</td>
<td>1.341 0.433 0.322 &lt; p &lt; 0.982 0.222 &lt; p &lt; 0.985</td>
</tr>
</tbody>
</table>


* The number of manufacturing sectors included for each pair-wise Pearson correlation with the U.S. is as follows: Belgium (8); Canada (9); Denmark (9); Finland (9); France (8); Germany (9); Italy (9); Japan (8); Netherlands (8); Norway (9); Sweden (9); and U.K. (8) Australia is excluded because a detailed classification for manufacturing sectors is not available.

* Confidence interval for the one-tail test of the null hypothesis H0: p = 0 against the alternative H1: p > 0 (positive correlation) at the 1% level, or for the one-tail test of the null hypothesis H0: p = p* against the alternative H1: p < p* (large correlation) at the 1% level.

* Confidence interval for the one-tail test of the null hypothesis H0: p = 0 against the alternative H1: p > 0 (positive correlation) at the 0.5% level, or for the one-tail test of the null hypothesis H0: p = p* against the alternative H1: p < p* (large correlation) at the 0.5% level.

* The employment concept used to calculate average wages is total employment instead of number of employees.
Confidence intervals are so wide - and remain so over time - that in every year they produce some cases of statistical indiscernibility between the extreme hypotheses of total independence and strong positive dependence. Moreover, the lack of a clear trend over time makes it rather difficult to find possible explanations for some of the observed patterns of industry wage differentials. For example, Belgium presents an industry wage structure which is almost perfectly similar to that of the U.S. in 1970 and completely different ten years later. Among the Scandinavian countries, which are very similar in many aspects included the organization of the labour market, Finland and Norway show a wage structure nearly identical to that of the U.S. over the entire period examined, while Sweden appears totally dissimilar in some years. Gittleman and Wolff suggest that unionization might be a significant factor in explaining cross-country differences in industry wage structures. However, Canada, France, and Japan, which are characterized by a very low union density like the U.S. (Freeman, 1988), have a completely different wage structure with respect to the U.S. in some years, but not in others.

A second method for assessing the degree of similarity of industry differentials across countries is to compute the coefficient of concordance among their wage structures. The values obtained by Gittleman and Wolff in all years between 1970 and 1985, for various numbers of countries and sectors, are given in Table 3.10. Also for this statistic, both samples representing only manufacturing sectors and samples including all industries are analyzed. Because of the wide variation in the national schemes of industry classification, the authors experimented several combinations in terms of number of countries (from 5 to 14) and number of sectors (from 8 to 20). In Table 3.10 I report the values of the coefficient of concordance only for the two limit cases of few countries and many sectors, and of many countries and few sectors. The other combinations considered by Gittleman and Wolff provide intermediate outcomes between these two extremes. From these results the authors infer that wage structures are quite similar and remain so over time, since all the coefficients exceed 0.60, they exceed 0.70 in most cases, and some of them are even equal to or greater than 0.80.
TABLE 3.10

Gittleman and Wolff's industry wage structure across countries*: estimated coefficients of concordance for selected countries and sectors and tests of their statistical significance, for *all industries" and manufacturing industries*.

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of countries (m)</th>
<th>Number of sectors (n)</th>
<th>All industries*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Number of countries (m)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Number of sectors (n)</td>
</tr>
<tr>
<td></td>
<td>Coefficient of concordance&lt;sup&gt;a&lt;/sup&gt;</td>
<td>F for H&lt;sub&gt;0&lt;/sub&gt;: ω = 0</td>
<td>p-value&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>1970</td>
<td>0.78</td>
<td>14.182</td>
<td>0.00000</td>
</tr>
<tr>
<td>1971</td>
<td>0.80</td>
<td>16.000</td>
<td>0.00000</td>
</tr>
<tr>
<td>1972</td>
<td>0.79</td>
<td>15.048</td>
<td>0.00000</td>
</tr>
<tr>
<td>1973</td>
<td>0.79</td>
<td>15.048</td>
<td>0.00000</td>
</tr>
<tr>
<td>1974</td>
<td>0.79</td>
<td>15.048</td>
<td>0.00000</td>
</tr>
<tr>
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<td>0.79</td>
<td>15.048</td>
<td>0.00000</td>
</tr>
<tr>
<td>1976</td>
<td>0.78</td>
<td>14.182</td>
<td>0.00000</td>
</tr>
<tr>
<td>1977</td>
<td>0.79</td>
<td>15.048</td>
<td>0.00000</td>
</tr>
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<td>1978</td>
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<td>14.182</td>
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<tr>
<td>1979</td>
<td>0.79</td>
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<td>0.78</td>
<td>14.182</td>
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</tr>
<tr>
<td>1983</td>
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</tr>
<tr>
<td>1984</td>
<td>0.80</td>
<td>16.000</td>
<td>0.00000</td>
</tr>
<tr>
<td>1985</td>
<td>0.80</td>
<td>16.000</td>
<td>0.00000</td>
</tr>
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</table>

(continued)
<table>
<thead>
<tr>
<th>Year</th>
<th>Coefficient of concordance</th>
<th>F for ( H_0: \omega = 0 )</th>
<th>p-value( ^d )</th>
<th>Coefficient of concordance</th>
<th>F for ( H_0: \omega = 0 )</th>
<th>p-value( ^d )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1970</td>
<td>0.76</td>
<td>22.167</td>
<td>0.00000</td>
<td>--</td>
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</tr>
<tr>
<td>1971</td>
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<td>19.923</td>
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<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>1972</td>
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<td>0.69</td>
<td>26.710</td>
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</tr>
<tr>
<td>1973</td>
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<td>0.00000</td>
<td>0.68</td>
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</tr>
<tr>
<td>1974</td>
<td>0.76</td>
<td>22.167</td>
<td>0.00000</td>
<td>0.68</td>
<td>25.500</td>
<td>0.00000</td>
</tr>
<tr>
<td>1975</td>
<td>0.83</td>
<td>34.176</td>
<td>0.00000</td>
<td>0.74</td>
<td>34.154</td>
<td>0.00000</td>
</tr>
<tr>
<td>1976</td>
<td>0.84</td>
<td>36.750</td>
<td>0.00000</td>
<td>0.72</td>
<td>30.857</td>
<td>0.00000</td>
</tr>
<tr>
<td>1977</td>
<td>0.85</td>
<td>39.667</td>
<td>0.00000</td>
<td>0.75</td>
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<td>1978</td>
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<td>0.00000</td>
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<td>1979</td>
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<td>0.73</td>
<td>32.444</td>
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<td>1980</td>
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<td>0.00000</td>
<td>0.76</td>
<td>38.000</td>
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</tr>
<tr>
<td>1981</td>
<td>0.89</td>
<td>56.636</td>
<td>0.00000</td>
<td>0.74</td>
<td>34.154</td>
<td>0.00000</td>
</tr>
<tr>
<td>1982</td>
<td>0.83</td>
<td>34.176</td>
<td>0.00000</td>
<td>0.74</td>
<td>34.154</td>
<td>0.00000</td>
</tr>
<tr>
<td>1983</td>
<td>0.84</td>
<td>36.750</td>
<td>0.00000</td>
<td>0.72</td>
<td>30.857</td>
<td>0.00000</td>
</tr>
<tr>
<td>1984</td>
<td>0.86</td>
<td>43.000</td>
<td>0.00000</td>
<td>0.70</td>
<td>28.000</td>
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<tr>
<td>1985</td>
<td>0.87</td>
<td>46.846</td>
<td>0.00000</td>
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<td>--</td>
</tr>
</tbody>
</table>

\( ^a \) Source: Gittleman and Wolff (1993, p.305, Table 5).

\( ^b \) The countries and sectors included for the coefficients of concordance using all industries are as follows: 5 countries, 20 sectors; countries included are Denmark, Finland, Norway, Sweden and the U.S.; sectors included are agriculture; mining and quarrying; food, beverages and tobacco; textiles, wood and wood products; paper, printing and publishing; chemicals; non-metallic mineral products; basic metal products; machinery and equipment; other manufactured products; electricity, gas and water; construction; wholesale and retail trade; restaurants and hotels; transport, storage and communication; finance and insurance; real estate; community, social and personal services; producers of government services.

\( ^c \) The countries and sectors included for the coefficients of concordance using only manufacturing industries are as follows: 8 countries, 9 sectors; countries included are Canada, Denmark, Finland, Germany, Italy, Norway, Sweden and the U.S.; sectors included are food, beverages and tobacco; textiles, wood and wood products; paper, printing and publishing; chemicals; non-metallic mineral products; basic metal products; machinery and equipment; other manufactured products.

\( ^d \) P-values for the one-tail test of the null hypothesis \( H_0: \omega = 0 \), against the alternative hypothesis \( H_1: \omega > 0 \).
Contrary to the authors, who claim that industry wage rankings tend to become more similar over time. I think that no clear pattern for changes in similarity emerges from these samples. In order to verify their claim, I have estimated simple regressions of the coefficients of concordance on a time trend for all the cases (combinations of countries and sectors) presented by Gittleman and Wolff (1993, p.305, Table 5). The hypothesis of existence of a positive time trend in the coefficients of concordance is rejected, at the 1% level of significance, for half of the samples.

Tests of the null hypothesis $\omega = 0$ against the alternative $\omega > 0$, also presented in Table 3.10, show that the hypothesis of no agreement among wage rankings across countries is rejected in all cases at an extremely low significance level. As already observed in Section 3.3, however, these tests are not especially informative. The values obtained for the coefficient of concordance when all countries are compared simultaneously - generally ranging between 0.65 and 0.75 - are indeed indicative of a level of similarity which is rather difficult to classify as high or low.

Also in the case of cross-country comparisons we can hence argue that Krueger and Summers’s and Gittleman and Wolff’s conclusion about the remarkable similarity of industry wage structures is at least partly overstated. The actual degree of association among industry wages in different countries, in fact, seems to be of some intermediate degree between strong similarity and complete diversity in statistical terms. This ambiguity is considerably strengthened by the fact that the two studies provide contradictory results. Some of the Pearson correlations presented in the two articles, and previously described, are summarized in Table 3.11 and graphed in Figure 3.6. They refer to correlations between the industry wage structure for manufacturing sectors of the U.S. and that of other 7 countries considered in both studies. The reference years are 1982, for Krueger and Summers’s analysis, 1980 and 1985, for Gittleman and Wolff’s analysis. We could expect the values for 1982 to be between those for 1980 and 1985, if we believed in the existence of some steady pattern over time, or at least to be close to the values for 1980 and 1985. Figure 3.6 shows instead that the correlations calculated by Krueger and Summers are, in most cases, considerably different from those obtained by Gittleman and Wolff. For example, the Pearson correlation between the U.S. and France is quite high for Krueger and Summers’s sample and rather low in Gittleman and Wolff’s case, especially in 1985. On the other hand, the lowest of all correlations found by Krueger and Summers is the one between the U.S. and Norway, while
### TABLE 3.11

Comparison between Krueger and Summers' and Gittleman and Wolff's industry wage structures across countries: estimated Pearson correlation coefficients with the U.S. industry wage structure for manufacturing industries

<table>
<thead>
<tr>
<th>Country</th>
<th>Krueger and Summers' correlations</th>
<th>Gittleman and Wolff's correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canada</td>
<td>0.92</td>
<td>0.93</td>
</tr>
<tr>
<td>France</td>
<td>0.90</td>
<td>0.82</td>
</tr>
<tr>
<td>Germany</td>
<td>0.85</td>
<td>0.89</td>
</tr>
<tr>
<td>Japan</td>
<td>0.89</td>
<td>0.86</td>
</tr>
<tr>
<td>Norway</td>
<td>0.67</td>
<td>0.96</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.82</td>
<td>0.80</td>
</tr>
<tr>
<td>U.K.</td>
<td>0.95</td>
<td>0.88</td>
</tr>
</tbody>
</table>

* Source: Krueger and Summers (1987, p. 26, Table 2.3).
* Source: Gittleman and Wolff (1993, p. 303, Table 4).

For Krueger and Summers' correlations, the number of manufacturing sectors is assumed to be 17 for all countries (see footnote b of Table 3.7). For Gittleman and Wolff's correlations, the numbers of manufacturing sectors included are as follows: Canada (9); France (8); Germany (9); Japan (8); Norway (9); Sweden (9); and U.K. (8).

### FIGURE 3.6

Krueger and Summers' and Gittleman and Wolff's industry wage structures across countries: Pearson correlation coefficients with the U.S. industry wage structure
for the same pair of countries Gittleman and Wolff estimate the highest correlation both in 1980 and in 1985. Statistical outcomes seem to be highly dependent on the data sources, the samples, and the variables employed. I believe, therefore, that some caution should be used in drawing conclusions based on this sort of simple statistics.

3.5 Aggregate Industry Wage Data versus Micro Data Analyses

In the preceding Sections, I have tried to challenge the reliability of empirical evidence based on aggregate data from the point of view of the actual statistical meaning of the values obtained for the various measures of association used to judge the degree of stability over time and across countries of industry wage structures. In this Section, I will examine the general conceptual limitations faced by inter-temporal and cross-country comparisons based on aggregate industry wage data, as compared to analyses which utilize, instead, data at the individual level.

A first problem which emerges when using aggregate wage data is that average wages by industry ignore the variance of individual wages about this average within each industry. Industry wage structures estimated in a regression approach with individual data, instead, also take into account the dispersion of wages within industries. When we want to compare inter-industry wage structures in two different countries (or in two different years for the same country) through correlations, if the variance of individual wages within industries is not the same for the two countries (or the two years), but average industry wages are similar, aggregate data tend to show a higher degree of similarity than micro data.

The relevance of this issue can be illustrated by a simple example constructed with three artificial samples of data for individual wages. The data and the results of the experiment are presented in Table 3.12. The three samples can be regarded as representing three different countries or, alternatively, three different points in time for the same country. These extremely simplified imaginary economies have three industry sectors, the first employing 5 workers, the second 20 workers, and the third 16 workers. Their individual wages are given in the first part of Table 3.12. Sample A is characterized by a variance of wages within industries equal to zero, that is all workers in an industry are paid exactly the same wage. Sample B and sample C are instead characterized, respectively, by a high and a very high variance of wages within industries. All three samples, however, have identical
TABLE 3.12
Simulated data for individual wages and estimated inter-industry wage differentials

<table>
<thead>
<tr>
<th>Industry 1</th>
<th>SAMPLE A: zero variance</th>
<th>SAMPLE B: high variance</th>
<th>SAMPLE C: very high variance</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>50</td>
<td>30</td>
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<td>2</td>
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<td></td>
<td>50</td>
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<table>
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<tbody>
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</tr>
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(continued)
TABLE 3.12 (continued)

<table>
<thead>
<tr>
<th>SAMPLE A:</th>
<th>SAMPLE B:</th>
<th>SAMPLE C:</th>
</tr>
</thead>
<tbody>
<tr>
<td>zero variance</td>
<td>high variance</td>
<td>very high variance</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Average wage industry 1: $w_1$ | 50 | 50 | 50 |
Average wage industry 2: $w_2$ | 100 | 100 | 100 |
Average wage industry 3: $w_3$ | 300 | 300 | 300 |
Variance of wages industry 1: $s^2_{w1}$ | 0 | 200.0 | 9216.0 |
Variance of wages industry 2: $s^2_{w2}$ | 0 | 4607.5 | 22410.0 |
Variance of wages industry 3: $s^2_{w3}$ | 0 | 1750.0 | 351742.4 |
Log average wage industry 1: $\ln w_1$ | 3.912 | 3.912 | 3.912 |
Log average wage industry 2: $\ln w_2$ | 4.605 | 4.605 | 4.605 |
Log average wage industry 3: $\ln w_3$ | 5.704 | 5.704 | 5.704 |
Average log wage industry 1: $\ln w_1$ | 3.912 | 3.869 | 1.652 |
Average log wage industry 2: $\ln w_2$ | 4.605 | 4.255 | 2.224 |
Average log wage industry 3: $\ln w_3$ | 5.704 | 5.694 | 2.223 |

Estimated industry dummy coefficients:

Industry 2: $\delta_2 = \ln \bar{w}_2 - \ln \bar{w}_1$ | 0.693 | 0.386 | 0.572 |
Industry 3: $\delta_3 = \ln \bar{w}_3 - \ln \bar{w}_1$ | 1.792 | 1.825 | 0.571 |

Estimated wage differentials in deviation form:

Industry 1: $D_1^*$ | -1.037 | -0.901 | -0.501 |
Industry 2: $D_2^*$ | -0.344 | -0.514 | 0.070 |
Industry 3: $D_3^*$ | 0.754 | 0.924 | 0.069 |

Wage differentials à la Gittleman and Wolff:

Industry 1: $D_1 = \ln w_1 - \ln \bar{w}$ | -1.099 | -1.099 | -1.099 |
Industry 2: $D_2 = \ln w_2 - \ln \bar{w}$ | -0.405 | -0.405 | -0.405 |
Industry 3: $D_3 = \ln w_3 - \ln \bar{w}$ | 0.693 | 0.693 | 0.693 |

Tests of normality of log wages:

Normality $\chi^2(2)$ for log wages all industries | 3.353 | 7.822 | 9.043 |
Normality $\chi^2(2)$ for log wages industry 1 | - | 0.458 | 1.227 |
Normality $\chi^2(2)$ for log wages industry 2 | - | 4.095 | 3.684 |
Normality $\chi^2(2)$ for log wages industry 3 | - | 0.940 | 3.780 |

* The $\chi^2$ test of normality of log wages fails to reject the null hypothesis at the 1% level in all cases. The 1% critical point is $\chi^2_{0.01}(2) = 9.210$. 

120
average industry wages. Although the three samples present quite different structures of individual wages, they can all be regarded as drawn from a log-normally distributed population of wages. The $\chi^2$ tests of normality of log wages in the whole samples, presented in the last part of Table 3.12, fail to reject the null hypothesis of normality in the population at the 1% significance level in all three cases. The hypothesis of log-normality of wages cannot be rejected at the 1% level also at the industry level for samples B and C. As already said, the distribution of wages within industries for sample A is instead uniform. Sample A represents an extreme, unrealistic case which will serve exclusively as a benchmark in evaluating the impact of variability of individual wages within industries on the measurement of the degree of similarity between industry wage structures.

Inter-industry wage differentials are estimated with simple regressions of the logarithm of individual wages on two dummy zero-one variables representing workers' affiliation to industry 2 and 3. The regressions also include a constant term. Differentials are then reported as deviations of the estimated industry dummy coefficients from the (employment-weighted) mean differential\(^{20}\). This way of expressing wage differentials is the one commonly adopted in the empirical literature utilizing micro data (for example, Borland and Suen, 1990; Edin and Zetterberg, 1992; Katz and Summers, 1989; Krueger and Summers, 1987, 1988; Winter-Ebmer, 1992; as well as the following Chapters of this thesis). The advantages of this normalization will be fully illustrated in Chapter 4. In the present context, it is sufficient to notice that this measure of industry wage differentials is comparable, in certain respects, with the variable for wage differentials used by Gittleman and Wolff (1993) and previously illustrated in Section 3.3 by equation (3.20). Specifically, industry differentials in deviation form derived from micro data are not equal to industry differentials à la Gittleman and Wolff derived from aggregate data, but the two measures provide evaluations of the degree of similarity between wage structures which can be directly comparable.

This can be seen by first considering the extreme case represented by a sample like sample A, where all workers are paid exactly the average wage $w_k$ of their industry

---

20 Since the wage regressions include a constant, I treat the omitted industry variable as having a zero effect on wages, calculate the employment-weighted average of the two estimated industry dummy coefficients, and report the difference between the industry coefficients and this weighted average. The differential for industry 1 (the omitted dummy) is equal to minus the employment-weighted average. The resulting statistics represent, therefore, the proportionate difference between an employee in a given industry and the average employee in the whole economy (Krueger and Summers, 1988).
Industry differentials in deviation form can be obtained by: (i) estimating a regression of log individual wages on a constant and (K-1) industry dummies, where the dummy for industry \(k = 1\) is omitted to avoid perfect multicollinearity between the regressors and the constant term.

\[
\ln w_i = \hat{\alpha} + \sum_{k=2}^{K} \hat{\delta}_k d_{ik}, \quad i = 1, ..., N; \tag{3.21}
\]

(ii) calculating the employment-weighted average of the estimated industry dummy coefficients \(\hat{\delta}_k\), including a coefficient equal to zero for industry 1 (so its coefficient \(\hat{\delta}_1 = 0\) does not affect the weighted average, but its employment \(n_1\) does),

\[
\bar{\delta}^{e-w} = \frac{\sum_{k=1}^{K} n_k \hat{\delta}_k}{\sum_{k=1}^{K} n_k}, \tag{3.22}
\]

where \(n_k\) is employment in industry \(k\) and \(\sum_{k=1}^{K} n_k = N\) is total employment; (iii) taking the differences between each estimated industry dummy coefficient \(\hat{\delta}_k\) and this weighted average,

\[
D_k^* = \hat{\delta}_k - \bar{\delta}^{e-w}, \tag{3.23}
\]

for all \(K\) industries, so that the differential for industry 1 is \(D_1^* = 0 - \bar{\delta}^{e-w} = -\bar{\delta}^{e-w}\).
Given the nature of the estimated regression (3.21) - it includes only industry dummy variables as regressors - the industry dummy coefficients $\hat{\delta}_k$ have a particular meaning; they represent the difference between the average log wage (the average of the dependent variable) in industry $k = 2, ..., K$ and the average log wage in industry 1 (the omitted industry).

\[
\hat{\delta}_k = \ln w_k - \ln w_1,
\]  \hspace{1cm} (3.24)

where $\ln w_k = \frac{1}{n_k} \sum_{j=1}^{n_k} \ln w_{jk}$, over the $j = 1, ..., n_k$ workers in industry $k$. This characteristic of a dummy variable model is fully illustrated in the general Appendix to the thesis, so one can refer to it for a more detailed explanation. Since in this particular case (zero variance) all workers in an industry are paid the same wage $w_k$, $w_k$ is also the average wage of that industry and the average log wage is equal to the log average wage.

\[
\ln w_k = \ln w_k.
\]  \hspace{1cm} (3.25)

Substituting (3.25) into (3.24) and then this back into the definition of differential in deviation form (3.23), I obtain:

\[
D_k^* = \ln w_k - \ln w_1 - \left[ \frac{\sum_{k=1}^{K} n_k (\ln w_k - \ln w_1)}{\sum_{k=1}^{K} n_k} \right]
\]

\[
= \ln w_k - \ln w^{*\text{w}}.
\]  \hspace{1cm} (3.26)
where $\ln w^e_w = \left( \frac{\sum_k n_k \ln w_k}{\sum_k n_k} \right) / \left( \frac{\sum_k n_k}{\sum_k n_k} \right)$ is the employment-weighted average of log average wages by industry.

According to the definition of wage differential used by Gittleman and Wolff (1993), I have instead:

$$D_k = \ln w_k - \ln \bar{w}, \quad (3.20')$$

where $\bar{w} = \left( \frac{\sum_i w_i}{N} \right) = \left( \frac{\sum_k w_k}{K} \right)$ is the average wage over all workers in the whole sample. So, even in this extreme case of no dispersion of wages within industries at all, differentials from micro data $D^*_k$ are not the same as differentials à la Gittleman and Wolff $D_k$. However, the sample variances across the $K$ industries of $D^*_k$ and $D_k$ are identical, both being simply equal to the sample variance among the log average wages $\ln w_k$:

$$s^2_{D^*} = \frac{\sum_{k=1}^K (D^*_k - \bar{D}^*)^2}{K - 1} = \frac{\sum_{k=1}^K \left( \ln w_k - \ln w^e_w - \frac{1}{K} \sum_k \ln w_k + \ln w^e_w \right)^2}{K - 1} \quad (3.27)$$

$$s^2_{\ln w} = \frac{\sum_{k=1}^K (\ln w_k - \ln \bar{w})^2}{K - 1} = s^2_{\ln w},$$

124
\[ s_D^2 = \frac{\sum_{k=1}^{K} (D_k - \bar{D})^2}{K - 1} \]
\[ = \frac{\sum_{k=1}^{K} (\ln w_k - \ln \bar{w} - \frac{1}{K} \sum_{k=1}^{K} \ln w_k + \ln \bar{w})^2}{K - 1} \]
\[ = \frac{\sum_{k=1}^{K} (\ln w_k - \ln \bar{w})^2}{K - 1} \]
\[ = s_{\ln w}^2. \] (3.28)

An analogous identity holds for the sample covariances of industry wage differentials in two countries (or years) \( h \) and \( l \), that is for the covariance of \( D_k^h \) and \( D_k^l \), for the differentials from micro data, and the covariance of \( D_k^h \) and \( D_k^l \), for the differentials à la Gittleman and Wolff.

\[ s_{D^h, D^l} = s_{D^h, D^l} = s_{\ln w^h, \ln w^l}, \] (3.29)

and, as a consequence, for the sample Pearson correlations between industry wage differentials in two countries (or years),

\[ r_{D^h, D^l} = r_{D^h, D^l} = r_{\ln w^h, \ln w^l}. \] (3.30)

Incidentally, this shows that Gittleman and Wolff's transformation of log average industry wages into wage differentials by (3.20), for the mere purpose of calculating correlations between countries (or years), is useless. They could have well used log average
wages directly, as Krueger and Summers (1987) do. The transformation of \( \ln w_k \) into the differentials \( D_k \) just implies re-scaling the vector of log average wages by a constant \( \ln \tilde{w} \), which does not affect the observed measures of dispersion and association\(^1\).

Equation (3.30) shows that the Pearson correlation between wage differentials in deviation form based on micro data, \( r_{D_i^*,D_i^*} \), the Pearson correlation between wage differentials \( \text{à la} \) Gittleman and Wolff (1993) based on aggregate data, \( r_{D_k^*,D_k^*} \), and, indeed, even the Pearson correlation between simple log average wages \( \ln w_k \) based on aggregate data \( \text{à la} \) Krueger and Summers (1987), \( r_{\ln w_k^*,\ln w_k^*} \), are identical. In the special case of no variance of wages within industries, therefore, the three measures \( D_k^* \), \( D_k \) and \( \ln w_k \) provide evaluations of the degree of similarity between countries (or years), through Pearson correlations, that are perfectly comparable. A similar comparability of results holds for \( D_k^* \) (from micro data), \( D_k \) (\text{à la} Gittleman and Wolff) and \( \ln w_k \) (\text{à la} Krueger and Summers) in terms of rank statistics like the Spearman correlation or the coefficient of concordance. Since \( D_k^* \) and \( D_k \) are both obtained from the re-scaling \( \ln w_k \) by a constant that does not change across industries (even if a different constant in the two cases, see equations (3.26) and (3.20')), the two alternative transformations do not modify the original rankings of wages and the respective rank measures of association.

The situation changes when one proceeds to consider the more realistic case of a sample like samples B or C, where there is some variability of individual wages within industries. Differentials in deviation form derived from a regression with micro data are still defined by equation (3.23), but now the average log wage \( \bar{\ln w_k} = \frac{1}{n_k} \sum_{j=1}^{n_k} \ln w_{kj} \) in industry

\(^1\)Actually, in their Table 1, Gittleman and Wolff (1993, p.298) report the values of industry differentials \( D_j \), but only for one year (1985) and three countries (the U.S., German and Japan). In this case differentials, rather than log average industry wages, may be more interesting and easier to interpret. But in all the other 5 tables of their article, involving 14 different countries and the time period 1960-85, they exclusively present correlations, coefficients of concordance and regression results based on wage differentials. So the greatest emphasis (even in Table 1) is definitely laid on measures of variability and association among wage differentials, which are not affected by the transformation.
$k$ is no longer equal to the log average wage $\ln w_k = \ln \left( \frac{1}{n_k} \sum_{j=1}^{n_k} w_{jk} \right)$ of that industry, since $w_{jk} \neq w_{ik}$ for at least one $j \neq i$. So, for two countries (or years) $h$ and $l$, equation (3.26) becomes:

$$\begin{align*}
D^h_k &= \ln w^h_k - \ln w^{e-w,h} \\
D^l_k &= \ln w^l_k - \ln w^{e-w,l},
\end{align*}$$

(3.26*)

where $\ln w^h_k$ and $\ln w^l_k$ are the average log wages of industry $k$ in country $h$ and $l$ respectively, and $\ln w^{e-w,h} = \left( \frac{\sum_{k=1}^{K} n^h_k \ln w^h_k}{\sum_{k=1}^{K} n^h_k} \right)$ and $\ln w^{e-w,l} = \left( \frac{\sum_{k=1}^{K} n^l_k \ln w^l_k}{\sum_{k=1}^{K} n^l_k} \right)$ are the employment-weighted averages of average log wages in country $h$ and $l$ respectively.

On the other hand, differentials $a la$ Gittleman and Wolff for the two countries remain as defined in equation (3.20'):

$$\begin{align*}
D^h_k &= \ln w^h_k - \ln \bar{w}^h \\
D^l_k &= \ln w^l_k - \ln \bar{w}^l,
\end{align*}$$

(3.20'')

where $\ln w^h_k$ and $\ln w^l_k$ are the log average wages of industry $k$ in country $h$ and $l$ respectively, and $\bar{w}^h$ and $\bar{w}^l$ are the average wages over all workers in country $h$ and $l$ respectively.
Comparing the differentials from micro data in the case of variability of wages within industries - equation (3.26') - with those obtained in the previous case of no variability - equation (3.26) - I have by Jensen's inequality²²:

\[
\ln w_k \leq \ln w_k
\]  

(3.31)

and therefore \( \ln w^e \leq \ln w^e \), with the equal signs holding in the case of no variability within industries.

Equation (3.30), therefore, is no longer satisfied: the Pearson correlation of differentials à la Gittleman and Wolff \( r_{D^h, D^l} \) is still equal to the Pearson correlation of log average wages à la Krueger and Summers \( r_{\ln w^h, \ln w^l} \), but they are different from the Pearson correlation of differentials from micro data \( r_{D^h, D^l} \). In particular, if countries \( h \) and \( l \) have identical log average industry wages as in the example of Table 3.12,

\[
\ln w^h_k = \ln w^l_k, \quad \forall k = 1, ..., K,
\]  

(3.32)

the correlations à la Gittleman and Wolff and à la Krueger and Summers are equal to one,

\[
r_{D^h, D^l} = r_{\ln w^h, \ln w^l} = 1.
\]  

(3.33)

²²Jensen's inequality states that if \( U(x) \) is strictly concave and \( X \) is a non-degenerate random variable, then

\[
E[U(X)] < U[E(X)]
\]

where \( E \) is the expectation operator (Lambert, 1993).
But given equation (3.31), we have in general:

\[ \ln w_k^h \neq \ln w_k^l, \]  

(3.34)

unless individual wages within industry \( k \) are identically distributed in country \( h \) and country \( l \), in which case they would have the same variance. So, if the variance of wages within industry \( k \) in country \( h \) is different from that in country \( l \), equation (3.34) is always satisfied and the correlation of differentials in deviation form from micro data is:

\[ r_{D^*, D^''} < 1. \]  

(3.35)

Returning to the example in Table 3.12, if log average industry wages \( \ln w_{1,2,3} \) were used, like in Krueger and Summers's and Gittleman and Wolff's studies, the samples examined would lead to the conclusion that the three industry wage structures are perfectly identical. When industry wage differentials estimated from micro data \( D_{1,2,3}^* \) are instead considered, results are quite different. The Pearson correlation between wage differentials estimated with samples A and sample B is 0.98, that between industry differentials obtained from samples A and C is 0.79, and that between wage differentials estimated with samples B and C is 0.66. If the variance of individual wages within industries is equal to zero, correlations between industry wage structures based on aggregate data and on micro data are identical and therefore perfectly comparable. If industry wage structures are instead characterized by the same average industry wages but by different positive variances of individual wages within industries, correlations based on aggregate data show a higher degree of similarity than correlations based on micro data. The comparability of the two types of correlation will depend on how close we are to the case of no variability of individual wages within industries, since correlations based on aggregate data - differently from those based on micro data - will not take this variability into account.
A second and crucial limitation met by analyses of the inter-industry wage structure based on aggregate average data is that they do not take into account possible differences in workers' human capital and working conditions. If the distribution by industry of human capital characteristics and of working conditions varies across countries (or over time for the same country), this may "conceal", at an aggregate level, the true structure of industry wage differentials of a non-competitive nature, like those ascribable to efficiency wages or insiders-outsiders considerations. This point can be illustrated again with a simple example. Suppose that we are trying to compare the wage structures of two countries, indicated as A and B, with only two productive sectors. Assume that, at an average aggregate level, both country A and country B exhibit large and positive differentials for industry 1 and large and negative differentials for industry 2. Their wage structures, evaluated through average wages, appear thus very similar. But suppose that the observed differentials in country A are due to the fact that there is a concentration of highly skilled workers in industry 1 and a concentration of unskilled workers in industry 2, while in country B the distribution of skilled and unskilled workers is homogeneous across the two industries. When one takes into account these differences in workers' human capital at an individual level, the true differentials of non-competitive nature for country A become indeed smaller in absolute size, while the differentials for country B remain unchanged. The two countries appear thus more dissimilar than in the case of an analysis based on aggregate data: in country A, equal workers are paid equal wages, while in country B they are not. An approach based on aggregate wage data ignores differences in the distribution of human capital and working conditions and if these characteristics of individual workers are positively correlated with their wages - as they are, according to human capital theory - aggregate data tend to overestimate the degree of similarity between wage structures of a non-competitive nature. If we instead examine industry wage structures through individual data in a regression approach, we have the possibility to correct for these differences and evaluate the exact nature of the observed wage differentials.

The fact that correlations between industry wage structures based on aggregate data are usually larger than those based on micro data and a regression approach has already been observed by other authors (for example, Borland and Suen, 1990; Edin and Zetterberg, 1992) and will emerge at various stages in the following Chapters. The considerations presented in this Section try to provide possible rationales of these results and to show why empirical
evidence obtained from micro data is essential for the type of investigation which is the object of this thesis and that I have introduced in Chapter 2.

3.6 Conclusions

Krueger and Summers conclude their analysis of the regularities in the inter-industry wage structure by asserting,

"The evidence [...] indicates the presence of pervasive regularities in the wage structure. A similar industrial pattern of wages recurs in different eras and different places [...]. Such a uniform pattern ought to be explicable without resort to highly idiosyncratic factors specific to particular workers, industries, times or places. [...] [This] cannot plausibly be rationalized without the introduction of non-competitive considerations or additional constraints [...]." (Krueger and Summers, 1987, p.37).

Two objections can be raised about these remarks. First, as I have tried to suggest in Sections 3.3 and 3.4 of this Chapter, care needs to be employed when interpreting the type of evidence provided in studies like those by Krueger and Summers (1987) and by Gittleman and Wolff (1993). The accuracy of simple measures of association is questionable in several cases and this casts some doubts about the claimed over-all stability of the industry wage structure across time and space. Second, empirical evidence based on average aggregate data may indeed be consistent with competitive explanations for inter-industry wage differentials. Before the observed wage structure can be regarded as supportive of the non-competitive theories, plausible competitive rationalizations such as compensating differentials and differences in labour quality and productivity - which could well lead to a stable pattern of wages across time and countries - must be ruled out. As suggested in Section 3.5, a more rigorous attempt to demonstrate the existence and measure the importance of industry wage differentials of an actually non-competitive nature requires a different approach: an empirical analysis based on micro data to test the relevance of industry affiliation in explaining relative wages after controlling for individual human capital characteristics and working conditions. As we will see in the following Chapters, this technique leads to conclusions which contradict those emerging from aggregate average industry wage data.
References


4.1 Introduction

In this Chapter I will start considering empirical evidence for inter-industry wage differentials based on micro data. Empirical analyses of the determinants of industry wage differentials using individual data were first provided for the U.S. labour market (Dickens and Katz, 1987a, 1987b; Katz and Summers, 1989; Krueger and Summers, 1987, 1988). According to these studies, industry wage differences appear to remain substantial even after controlling for a variety of human capital factors and working conditions. These results have been regarded as strongly supportive of non-competitive theories of wage determination like efficiency wage and insider-outsider theories, as illustrated in Chapter 2. After Krueger and Summers's (1988) seminal article, further evidence based on a very similar approach has become available for some other countries: Australia (Borland and Suen, 1990), Austria (Winter-Ebmer, 1992) and Sweden (Edin and Zetterberg, 1992). Even if some of the authors, in pair-wise cross-country comparisons, tend to concentrate more on the similarities rather than the dissimilarities between the U.S. and these other countries, their results are not totally unambiguous. Clear differences among countries in terms of size, statistical significance and variability of industry wage differentials seem to emerge. Moreover, if one takes a more comprehensive view of this kind of international evidence, these differences seem to be
related to country specific institutional conditions of the type presented in Chapter 2, as openly recognized also by Edin and Zetterberg (1992) about the Swedish case.

In this Chapter I will present evidence for Germany based on the individual data available from the German Socio-Economic Panel (SOEP). The approach here adopted is also similar to Krueger and Summers's (1988) and essentially consists in the estimation of a wage equation which includes measures of human capital and working conditions, as well as industry affiliation controls, as explanatory variables. This method permits an evaluation of competitive and non-competitive influences on the process of wage determination and the resulting inter-industry structure of relative wages, as explained in Chapter 2. My empirical analysis of the German case, however, differs from Krueger and Summers's study in a number of methodological aspects. The most relevant of these is the use of a different estimation technique, the Heckman's two-stage model for sample selection bias (Heckman, 1979) rather than a simple OLS regression. This choice is induced by a feature specific to the German data-set and the way it records information about individual wages and working hours. In the attempt to define a dependent hourly wage variable for my model as accurate as possible, a potential problem of sample selection bias arises due to the exclusion of overtime workers and Heckman's estimator represents the appropriate technique for a rigorous treatment of this problem. As we will see, industry differentials in Germany appear to be significant only to a limited extent. Differently from what emerges for the U.S. case, labour quality and other competitive factors have a major impact in explaining the observed wage structure. This suggests the possibility that, in the case of Germany, industry differences just reflect the effect of observable and unobservable characteristics of workers' human capital and working conditions.

Comprehensive empirical analyses of the stability of industry wage structures across countries have been based so far on aggregate industry wage data (Gittleman and Wolff, 1993; Krueger and Summers, 1987), in the way and with the limitations previously illustrated in Chapter 3. In this Chapter I will also consider cross-country comparisons of inter-industry wage structures as emerging from micro data, rather than from average industry data. I will contrast my results for Germany with those presented in the four earlier mentioned studies: for the U.S. by Krueger and Summers (1988); for Australia by Borland and Suen (1990); for Austria by Winter-Ebmer (1992); and for Sweden by Edin and Zetterberg (1992). All these articles make use of individual level data in a similar cross-sectional approach for one year
in the period 1983-86. My interest in comparing the wage dispersion across industries in these five countries derives from the fact that they are usually considered as spanning a wide range of different labour market institutional structures and, in particular, of different degrees of centralization of wage bargaining, as suggested in Chapter 2. In contrast with what emerges from aggregate data, empirical evidence based on micro data emphasizes cross-country differences and the degree of centralization of wage bargaining may play a role in accounting for the observed pattern of industry wages.

The rest of the Chapter is structured as follows. Section 4.2 describes the main features of the German Socio-Economic Panel data-set (SOEP), the characteristics of the sub-sample of interest for my empirical analysis, the specification of the econometric model adopted, and the construction of the dependent and explanatory variables involved in this specification. In Section 4.3 I show and evaluate the main findings of the analysis of German inter-industry wage differentials obtained with data from the SOEP. In Section 4.4 I compare my empirical evidence for Germany with that available from micro data for the U.S., Australia, Austria and Sweden through Pearson product-moment and Spearman rank correlation analysis. Section 4.5 contains some concluding remarks.

4.2 Data, Sub-Sample Characteristics, Model Specification and Construction of the Variables

My empirical analysis of industry wage differentials in Germany is based on individual cross-sectional data from the 1984 wave (Wave 1) of the German Socio-Economic Panel (SOEP). The panel provides representative longitudinal data on income, transfer payments, labour market experience, changing family composition and housing for individuals, families and households. It also allows representative cross-sectional analyses. The sample on which the SOEP is based is representative of the entire population in Germany. All household

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23 The SOEP is constructed and maintained by the Sonderforschungsbereich 3 'Mikroanalytische Grundlagen der Gesellschaftspolitik' at the Universities of Frankfurt and Mannheim, in collaboration with the Deutsches Institut für Wirtschaftsforschung (DIW) in Berlin. The fieldwork is done by Infratest Sozialforschung, a survey institute in Munich. The project is funded by the Deutsche Forschungsgemeinschaft (DFG) in Bonn (Hanefeld, 1984).

24 Initially - and therefore in 1984, the year I consider in my analysis - the SOEP sample was designed to be representative of the entire population in West Germany. One year after German unification, the sample has
members 16 years old or older are interviewed annually, from 1984 onwards, in about 6,000 households. The survey relies on two different types of questionnaire: the first collects information about the household as a whole; the second, which is the relevant one for the purpose of my study, is addressed to each individual household member 16 years old or older and contains detailed questions about participation in gainful employment (Hanefeld, 1984).

Because of the importance of guest-workers in the German economy, both Germans and foreigners living in Germany are represented in the SOEP. The number of foreigners included in the survey sample is over-representative of the actual proportion of foreigners in the population. In the sub-sample of workers used in the present study, foreigners are about 39% of the whole sub-sample. This is due to the purpose of the SOEP of providing a specific sample of foreigners which is by itself representative of the entire universe of guest-workers in Germany, to allow separate analyses. In order to take this peculiarity of the survey into account, I construct for my regression analysis special variables apt to capture at least a part of the distinctive aspects of foreign workers human capital, such as the variables for modelling foreign education and, more generally, dummy variables for foreign nationalities.

The wage variable I want to use in my regression analysis is a measure of standard hourly earnings for salaried workers regularly employed in agricultural, industrial and service firms, both in the private and in the public sector. The measure of earnings available in the data-set is not independent from the hours of work, which may vary across individuals, firms, and sectors. Usual hourly earnings provide therefore a measure of the wage rate which is more properly comparable across industries. Moreover, I consider only regularly salaried workers, since the focus of the present study is on the behaviour of employers and their employees in the process of wage determination. I also decided to concentrate on a sample of male workers only to avoid the problem of self selection connected with female labour supply, illustrated in Chapter 2.

The initial sample of all male individuals 16 years old or older contains 6,007 observations. The sub-sample I analyse is composed of German and foreign male employees been enlarged to include also ex-East German households and be representative of the population of the whole unified Germany.

25 The sample for Wave 1-1984 of the SOEP contains exactly 5,921 households.
selected according to the criteria reported in the following list. A detailed description of all
the SOEP variables involved in the selection procedure is provided in Appendix 4.A.

i) Individuals younger than 65 years, the normal age of retirement in Germany - this selection
reduces the sample to 5,498 observations (about 92% of the initial sample).

ii) Full-time or regular part-time private and public employees, excluding individuals not in
the labour force, unemployed and irregularly employed workers - this selection reduces the
sample to 4,141 observations (about 69% of the initial sample, with a reduction of -25% with
respect to the previous sub-sample).

iii) Blue- and white-collar workers, excluding professional men, self-employed workers,
trainees and civil servants qualified as Beamten, who being public officials are subject to
peculiar regulations affecting their position in the labour market (e.g. clerical officers, judges,
career military personnel) - this selection reduces the sample to 3,368 observations (about
56% of the initial sample, with a reduction of -19% with respect to the previous sub-sample).

iv) Employees working a fixed number of hours per week, for whom the measure of usual
hourly earnings is more exactly determined and less subject to measurement errors - this
selection reduces the sample to 3,240 observations (about 54% of the initial sample, with a
reduction of -4% with respect to the previous sub-sample).

My empirical approach is to estimate a standard cross-section wage equation in the
framework of the earnings function of human capital theory (Becker, 1967; Mincer, 1974),
enriched by demographic and working conditions variables and by industry dummy variables.
Following the strategy illustrated in Chapter 2, in order to examine the importance of industry
affiliation in explaining relative wages, I want to evaluate the effects of industry dummy
variables after controlling for human capital, demographic background, and working
conditions as well as possible. Under the hypothesis of a competitive model - if the list of
controls is complete - the estimated coefficients of industry dummy variables would not be
significantly different from zero. The general structure of the wage regression model is of the
following form:

$$\ln w_i = \beta' x_i + \gamma' y_i + \delta' d_i + e_i, \quad i = 1, ..., N,$$

(4.1)
where \( w_i \) is the wage of individual \( i \), \( x_i \) is a vector of human capital variables for individual \( i \), \( y_i \) is a vector of demographic and working conditions variables for individual \( i \), \( d_i \) is a vector of \((K-1)\) - assuming that the model includes a constant term \( \beta_0 \) - industry dummy variables for individual \( i \)'s affiliation to industry \( k \), and \( e_i \) is a random disturbance term assumed to be normally distributed with zero mean and constant variance \( \sigma^2_e \). The regression parameters \( \beta \), \( \gamma \) and \( \delta \) can be estimated with the OLS method.

The existence of statistically significant industry effects in a wage regression like (4.1) however, is not a definite proof in support of non-competitive theories of wage determination. Unmeasured labour quality differences - such as ability and motivation - which might vary systematically across industries, and unmeasured differences in industry specific working conditions, which necessitate compensating wage differentials, may indeed induce biased estimates of the coefficients of the industry dummy variables. This might lead to an overestimate of the pure industry affiliation effect in explaining the observed wage structure. It is therefore crucial to incorporate the whole information available from the data in the set of control variables included in the wage regression, in the attempt to - at least - minimize the bias due to omitted variables.

For the empirical construction of the wage rate variable \( w_t \), a measure of earnings and a measure of hours of work are required. The relevant information on earnings given in the questionnaire refers to gross earnings in the month preceding that of the interview, excluding special payments - such as vacation bonuses or back pay - but including pay for overtime. Two different measures of hours worked are given: hours actually worked weekly, on average, in the month preceding that of the interview, including overtime, and normal hours worked weekly, excluding overtime. Both measures include transitory components, such as sick time or vacation days, as normal work time. There is a possible problem in computing standard hourly earnings that arises due to the non-linearity of total earnings as a function of hours actually worked when overtime work is done\(^{26}\). I therefore consider only a sub-sample of

\(^{26}\) Even if a constant wage rate is earned over all hours normally worked each week, this need not imply that the wage rate obtained by working overtime hours equals the individual's average wage rate. It may therefore be that additional hours worked overtime would change the marginal and the average wage rate. Unfortunately, the SOEP does not provide information on this issue, but only a measure of total earnings including payments for overtime work.
straight-time employees, defined as individuals who did not work overtime hours in the relevant period. The wage rate variable is thus constructed as gross earnings in the last month divided by four times the normal hours worked weekly, where neither the earnings measure nor the hours of work measure are affected by overtime work. I first eliminate from the sample all the observations for which information on earnings and/or hours of work are missing. This reduces the sample to 2,945 observations (about 49% of the initial sample, with a reduction of -9% with respect to the previous sub-sample). Then I eliminate individuals who report normal hourly earnings less than 1 DM, considered to be outliers. This reduces the sample by only 1 observation. The subsequent selection of the sub-sample of straight-time employees leads to a final sample size of 2,072 observations (about 34% of the initial sample, with a reduction of -30% with respect to the previous sub-sample).

The exclusion of overtime workers from the sub-sample may raise two problems related to the possible non-randomness of the selected sample. First, it might be the case that overtime workers are not proportionally distributed across industries. A higher wage rate might be systematically associated with more compensated overtime work or, on the contrary, the usual wage rate might be relatively lower for individuals who do work overtime. In both cases, the exclusion of employees doing overtime work may disproportionately reduce the number of observations only in certain sectors - only in high wage sectors or low wage sectors respectively - thus reducing the precision of the respective estimated industry differentials. Second, such segmentation of the sample raises a serious risk of selection bias. The sample selection rule that determines the availability of data for the wage regression - only a sub-sample of straight-time workers is considered - may have critical consequences on the estimated coefficients. If observations are not excluded randomly, the wage function estimated on the selected sample confounds the parameters of interest with the parameters of the function determining the probability of entrance into the sample - i.e., the

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27 There is an additional reason to prefer an analysis of the straight-time sample. Earnings due to overtime work and especially hours actually worked weekly on average in the last month - including overtime hours - are likely to be seriously affected by measurement errors.

28 This implies a positive wage elasticity of overtime labour supply in face of short-run adjustments on the demand side.

29 Some indirect evidence of this negative wage elasticity of overtime labour supply is provided by Borjas (1980).
probability of not working overtime hours in the relevant period (Heckman, 1979). Under these circumstances, the OLS method gives biased estimates of the parameters of the wage equation and, among these, of the parameters relative to the industry dummy variables, which may lead to an incorrect evaluation of the relevance of industry affiliation in explaining relative wages.

A way to address the first problem is to construct a chi-square test to compare the distribution of employees across industries for the selected sub-sample with the distribution of employees across industries for a sample including both straight-time and overtime employees. The test gives the following result:\footnote{The classification of industry sectors considered for this chi-square test is the original one provided by the SOEP, which consists of 36 different industries. In my later regression analysis I use a different classification, an aggregation of the original into 26 sectors only.}

\[
\chi^2_{(35)} = 16.996 < \chi^2_{0.01(35)} = 57.342.
\]

We cannot therefore reject the null hypothesis of identical distributions and this can be interpreted as a signal that the overtime workers excluded from the sub-sample are proportionally distributed across industry sectors.

As far as the second problem is concerned, given the possibly serious effects arising from a sample selection bias, I adopt a rigorous treatment using the technique suggested by Heckman (1979). Heckman's two-stage estimator is consistent even when non-randomly selected samples are used to estimate behavioural relationships with simple regression methods, like least squares. The model that I consider, therefore, is not simply represented by equation (4.1), but by the following system of two equations with a selection criterion equation:

\[
\begin{align*}
\end{align*}
\]
\[ \ln w_i = \beta'x_i + \gamma'y_i + \delta'd_i + e_i, \]  

\[ \alpha^*_i = \alpha'z_i + e_{2i}, \quad i = 1, \ldots, N, \]  

(4.1')

(4.2)

where equation (4.1') is defined as equation (4.1) above, while \( \alpha^*_i \) is an unobserved index variable indicating the desired amount of overtime work done in the relevant period by individual \( i \). \( z_i \) is a vector of explanatory variables for the overtime work of individual \( i \), and \( e_{2i} \) is a random disturbance term normally distributed with zero mean and constant variance \( \sigma^2_{e_{2i}} \). The joint distribution of \( e_{1i} \) and \( e_{2i} \) is a bivariate normal and their covariance is \( \sigma_{e_{1i}e_{2i}} \).

Observations on the wage rate \( w_i \) are included in the sub-sample if \( \alpha^*_i = 0 \), while if \( \alpha^*_i > 0 \) they are excluded.

In the case of independence between \( e_{1i} \) and \( e_{2i} \) (\( \sigma_{e_{1i}e_{2i}} = 0 \)), so that the observations on \( w_i \) would be randomly excluded from the sub-sample, least squares estimators might be used to estimate \( \beta \), \( \gamma \) and \( \delta \) on the selected sample and the only cost of having an incomplete sample would be a loss in efficiency. But in the case of overtime work as a selection criterion, the probability of including observations on \( w_i \) in the sub-sample may vary with its value, or with the values of variables affecting \( w_i \); then the probability of observing \( w_i \) will depend on \( e_{1i} \). \( \sigma_{e_{1i}e_{2i}} \) will be different from zero and the sub-sample wage regression function will depend not only on \( x_i, y_i \) and \( d_i \), but also on \( z_i \). Under these circumstances, least squares estimators of \( \beta \), \( \gamma \) and \( \delta \) in equation (4.1') estimated on the selected sample will be biased, as in an ordinary problem of omitted variables (Heckman, 1979). An important source of selection bias is represented by the omission of variables in \( z_i \) not

\[ ^{31} \text{Moreover, if } \sigma_{e_{1i}e_{2i}} \neq 0 \text{, the usual formulae for standard errors of least squares coefficients are not appropriate: they underestimate the true standard errors and overstate estimated significance levels (Heckman, 1979, pp.157-58).} \]
contained in $x_i$, $y_i$ or $d_i$ - variables affecting the probability of observing $w_i$, but not $w_i$ directly - but correlated with these included variables. A symptom of selection bias is in fact that variables that do not belong to the true structural wage equation - variables in $z_i$ not in $x_i$, $y_i$ or $d_i$ - may appear to be statistically significant determinants of $w_i$ when they are incorrectly included as regressors in the wage equation and the wage regression is fitted on the selected sample (Heckman, 1979, p.155).

The selection rule implies that observations are excluded from the sub-sample if any overtime work is done, independently of its amount. In the context of my sample selection model, I am therefore interested in the probability that employees work any positive amount of overtime hours. I then build, for $o_t^*$, the counterpart binary variable $o_t^*$ according to the following criterion:

$$
\begin{align*}
    o_t^* &= 1 \text{ if } o_t^* > 0 \\
    o_t^* &= 0 \text{ if } o_t^* \leq 0
\end{align*}
$$

which substituted in equation (4.2) gives the binary probit selection equation:

$$
\begin{align*}
    o_t^* &= a'z_i + e_{2i}
\end{align*}
$$

Individuals then enter the sub-sample used to estimate equation (4.1') when $o_t^*$ is equal to 0, while they are eliminated when $o_t^*$ is equal to 1. The procedure followed for the construction of the binary variable $o_t^*$ and the SOEP variables involved are described in Appendix 4.A.

The solution proposed by Heckman (1979) consists of the following three steps:
i) apply probit analysis to equation (4.2') for the full sample, to estimate the parameters of the probability that $\alpha t_i = 1$ - the probability that any amount of overtime work is done - i.e., to estimate $\alpha / \sigma_e$:

ii) for each observation, estimate the Heckman's $\lambda$ in the form which is appropriate to the case of selection on the value 0 for $\alpha t_i$:

$$
\lambda_i = \frac{- \phi \left( \frac{\alpha' z_i}{\sigma_e} \right)}{1 - \phi \left( \frac{\alpha' z_i}{\sigma_e} \right)}, \quad (4.4)
$$

using the probit estimated coefficients for $\alpha / \sigma_e$; all of these estimators are consistent;

iii) estimate equation (4.1*) with OLS for the selected sub-sample, regressing $\ln w_i$ on $x_i$, $y_i$, $d_i$ and the estimated value of $\lambda_i$; regression estimators of equation (4.1') are consistent for $\beta$, $\gamma$, $\delta$ and $\sigma_{e_1 e_2} / \sigma_{e_2}$ - the coefficients of $x_i$, $y_i$, $d_i$ and $\hat{\lambda}_i$ respectively.

The sample selection bias introduced by eliminating employees working overtime hours is significant only if the coefficient for $\hat{\lambda}_i$ in the wage regression ($\sigma_{e_1 e_2} / \sigma_{e_2}$) is significantly different from zero, since this implies a significant covariance ($\sigma_{e_1 e_2} \neq 0$) between the wage regression and the selection equation disturbances $e_{1i}$ and $e_{2i}$.

As far as the choice of explanatory variables in equations (4.1*) and (4.2') is concerned, the set of human capital, demographic background, and working conditions controls used in the wage equation (4.1') ($x_i$ and $y_i$) includes: age; age squared; tenure in the current job (years); tenure squared; 5 dummies for German education - short-course secondary school, intermediate type of secondary school, technical high school or academically-oriented secondary school, technical college or engineering school, college or university (the base
group refers to employees who did not receive any education in Germany); 5 dummies for foreign education - compulsory school without final examination, compulsory school with final examination, further schooling, specialized professional school, college or university (the reference group consists of employees who did not receive any education outside Germany); 9 skill dummies - unskilled worker with on-the-job training, trained worker, foreman, master, white-collar industrial worker, white-collar worker in basic positions, white-collar worker with advanced qualifications, highly trained white-collar worker, white-collar worker with extensive leadership responsibilities (the excluded dummy variable represents unskilled blue-collar workers); 4 marital status dummies - married living with spouse, married permanently separated, divorced, widowed (the base group consists of single employees); the number of nights spent in a hospital in the previous year as a measure of health conditions; the degree of satisfaction with the current job in a scale from 0 to 10; and 3 dummy variables for the size of the firm of current employment - between 20 and 200 employees, between 200 and 2,000 employees, 2,000 or more (the reference group comprises employees in firms with fewer than 20 employees). The vector of variables that permits evaluation of the relevance of industry affiliation in explaining relative wages ($d_i$) includes 25 industry dummies (the omitted industry dummy represents employees working in the agriculture, forestry and fishery sector).

The age of individual workers is introduced among the explanatory variables of the wage equation as a proxy for their labour market experience. As we have seen in Chapter 2, according to human capital theory, a measure of work experience has an important role in accounting for the effect of costly investment in on-the-job training on earnings profiles (Mincer, 1974). In the case of the SOEP data, it is in fact possible to construct a direct measure of working experience using the biographical scheme available for each individual in Wave 1 (APBIO). The scheme records information about personal history from the age of 15 up to the present age and in particular whether the individual was engaged in full- or part-time employment in each year. Experimentation with the 1984 data, however, shows that working experience directly measured through the biographical scheme and age of individuals in the selected sub-sample are very strongly correlated (0.99). I therefore preferred to use the age variable, which is much easier to survey without measurement errors and to construct from the year of birth SOEP variable. The tenure of workers in their current job has a similar role in accounting for the effect on earnings of firm-specific forms of investment in human.
capital. Firm-specific training and skills are in fact supposed to have a greater impact on workers' productivity, the longer their job tenure in the same firm. The variables for education, the most direct form of investment in human capital as we have seen in Chapter 2, are here specified as a set of dummies representing educational qualifications. This approach, first adopted by Psacharopoulos and Layard (1979), permits a more detailed evaluation of rates of return to education. Earnings are better explained by educational qualification, rather than by years of full-time schooling, especially if part-time education represents an important form of investment in human capital. Two different sets of education variables are included. The first describes the highest level of education attained in Germany by both German and foreign workers. The second refers to the highest educational qualification obtained by foreign workers in their home country before migration. This second set of education dummies tries to capture aspects of human capital formation specific to guest-workers in Germany. The skill variables refer to the current occupational status of individual workers. They represent an attempt to approximate the actual level of individuals' working ability. Marital status dummies depict a demographic characteristic and background condition that may affect the marginal value of investment in human capital and the budget constraint faced by the individual. The amount of hospital treatment received in the previous year is introduced as a measure of physical human capital quality and as an indicator of working conditions. More dangerous and stressful jobs may in fact be associated with a more frequent resort to hospital care. The degree of satisfaction with the current job tries to measure working conditions in a more direct way. The use of job satisfaction as an economic variable in labour market analysis has been illustrated by Freeman (1978). Finally, the size of the firm of employment also gives some indication about working conditions. A more detailed explanation of the actual role of this variable will be provided at the end of Section 4.3.

The set of explanatory variables used in the overtime work probability equation (4.2') \((z_t)\) consists both of variables not included in the wage equation - assumed to affect the probability of working overtime hours but not affecting the wage rate directly - and of variables also included in the wage equation - assumed to influence simultaneously the probability of working overtime hours and the wage rate. The sub-set of non-overlapping variables affecting only the probability of working overtime is: the number of children under the age of 16 years living in the household; a dummy variable for a second house/apartment.
in the Federal Republic of Germany; a dummy variable for mortgages on the house/apartment which is the main residence of the household; and 5 nationality dummies - Turkish, Yugoslavian, Greek, Italian, other nationalities (the base group refers to German nationality employees). The number of young children, the ownership of a second residence and the existence of a mortgage on the main residence are all factors that may be positively related with a higher propensity to work overtime hours. Different nationalities of workers may also be associated with different propensities to work overtime. In particular, guest-workers may have a different attitude towards overtime work with respect to German workers. This sub-set of explanatory variables entering equation (4.2'), but not equation (4.1'), permits to identify any sample selection effect in the wage regression (4.1'). The sub-set of overlapping variables affecting both the probability of working overtime and the wage rate includes: age, age squared, 9 skill dummies, the number of nights spent in a hospital in the previous year, the degree of satisfaction with the current job, 3 dummy variables for the size of the firm of current employment, and the 25 industry dummies.

Other variables are used both in the wage equation and in the overtime work probability equation to deal with the problem of missing values. Instead of excluding observations with missing values in any of the explanatory variables - that would reduce further on the sample size (for example, missing values for industry affiliation are 191, 9.2% of the observations in the selected sub-sample) - I prefer to introduce a separate dummy variable for missing data about education, tenure, marital status, nationality, and industry affiliation. Dummy variables for missing values of education, tenure, and marital status are later eliminated from the model because their estimated coefficients are extremely small, not significantly different from zero at a very high significance level - that is, the effect of education, tenure, and marital status for individuals with missing values is not statistically different from the effect of the same variables for individuals whose characteristics define the base group of each dummy variable - and because their omission do not affect the other estimated coefficients. The construction of all explanatory variables appearing both in equation (4.1') and (4.2') and the SOEP variables involved are illustrated in Appendix 4.A.

Two different specifications of the sample selection model expressed by equations (4.1') and (4.2') are estimated: the first is the general model, which includes both control variables \((x_i, y_i)\) and industry dummies \((d_i)\) in the wage equation (4.1'); the second is
a restricted model, which involves only industry dummy variables \((d_i^*)\) in the wage equation (4.1'). In both specifications, equation (4.2') has the same form. With respect to the selection bias problem, the estimates give the following results: the coefficient for \(\hat{\lambda}_i\) in the wage equation fit on the selected sample for the general model is not significantly different from zero (the estimated \(\sigma_{\varepsilon_2}/\sigma_\varepsilon_2\) is -0.070, with a standard error of 0.078), indicating that I fail to reject the null hypothesis of no sample selection bias induced by the exclusion of employees working overtime hours; the coefficient for \(\hat{\lambda}_i\) in the wage equation for the restricted model is significantly different from zero at the 1% level (the estimated \(\sigma_{\varepsilon_2}/\sigma_\varepsilon_2\) is -0.164, with a standard error of 0.064), which implies that, in this case, I reject the null hypothesis of no sample selection bias. This last outcome is not unexpected: in the restricted model I exclude variables from the wage equation (the controls \(x_i\) and \(y_i\)) which, as we will see, are statistically significant determinants of the wage rate and many of these controls (the sub-set of overlapping variables in \(z_i\)) enter as explanatory variables the overtime work probability equation; \(\hat{\lambda}_i\), as a function of \(z_i\), proxies the effect on wages of these controls and hence its coefficient appears statistically significant in the wage equation merely because of their exclusion from the equation. Also in the case of the restricted model, however, Heckman's two-stage method guarantees consistent estimates of the parameters of equation (4.1'). The detailed results for the estimated probit overtime work equation and for the estimated wage equations, including \(\hat{\lambda}_i\) among the regressors, are presented in Appendix 4.B.

### 4.3 Basic Results

In Table 4.1 I report the results of cross-section estimates of inter-industry wage differentials in a sample selection model for an aggregation of three-digit industries according to the German industry classification, which is nearly comparable with the two-digit classification used by the other authors. The dependent variable is the logarithm of usual hourly earnings in the month of reference. As suggested by Krueger and Summers (1988), the estimated industry wage differentials are reported as deviations from the employment-weighted

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149
TABLE 4.1
Estimated wage differentials in a sample selection model for two-digit industries. 1984: deviations from the employment-weighted mean differential (unadjusted OLS standard errors in parentheses)

<table>
<thead>
<tr>
<th>Industry</th>
<th>Without controls</th>
<th>Standard errors</th>
<th>With controls</th>
<th>Standard errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Agriculture</td>
<td>-0.305</td>
<td>(0.082)</td>
<td>-0.109</td>
<td>(0.060)</td>
</tr>
<tr>
<td>2. Energy, water and mining</td>
<td>0.131</td>
<td>(0.076)</td>
<td>0.085</td>
<td>(0.057)</td>
</tr>
<tr>
<td>3. Chemical</td>
<td>0.136</td>
<td>(0.087)</td>
<td>-0.005</td>
<td>(0.063)</td>
</tr>
<tr>
<td>4. Rubber</td>
<td>-0.095</td>
<td>(0.083)</td>
<td>0.037</td>
<td>(0.062)</td>
</tr>
<tr>
<td>5. Stone, clay and glass</td>
<td>-0.009</td>
<td>(0.072)</td>
<td>0.021</td>
<td>(0.052)</td>
</tr>
<tr>
<td>6. Iron and steel</td>
<td>-0.053</td>
<td>(0.072)</td>
<td>0.061</td>
<td>(0.053)</td>
</tr>
<tr>
<td>7. Machinery, excl. elec.</td>
<td>0.049</td>
<td>(0.072)</td>
<td>0.061</td>
<td>(0.053)</td>
</tr>
<tr>
<td>8. Electrical machinery</td>
<td>0.062</td>
<td>(0.076)</td>
<td>0.030</td>
<td>(0.056)</td>
</tr>
<tr>
<td>9. Lumber, wood, paper and printing</td>
<td>-0.092</td>
<td>(0.079)</td>
<td>0.038</td>
<td>(0.057)</td>
</tr>
<tr>
<td>10. Textile and apparel</td>
<td>-0.046</td>
<td>(0.081)</td>
<td>0.014</td>
<td>(0.059)</td>
</tr>
<tr>
<td>11. Food, beverages and tobacco</td>
<td>-0.132</td>
<td>(0.081)</td>
<td>-0.101</td>
<td>(0.059)</td>
</tr>
<tr>
<td>12. Construction</td>
<td>-0.035</td>
<td>(0.072)</td>
<td>0.044</td>
<td>(0.053)</td>
</tr>
<tr>
<td>13. Wholesale trade</td>
<td>0.021</td>
<td>(0.095)</td>
<td>-0.078</td>
<td>(0.071)</td>
</tr>
<tr>
<td>14. Retail trade</td>
<td>-0.186*</td>
<td>(0.080)</td>
<td>-0.104</td>
<td>(0.059)</td>
</tr>
<tr>
<td>15. Railroads</td>
<td>-0.072</td>
<td>(0.105)</td>
<td>-0.070</td>
<td>(0.079)</td>
</tr>
<tr>
<td>16. Mail service</td>
<td>-0.014</td>
<td>(0.109)</td>
<td>0.011</td>
<td>(0.080)</td>
</tr>
<tr>
<td>17. Other transport and communications</td>
<td>0.002</td>
<td>(0.081)</td>
<td>0.011</td>
<td>(0.059)</td>
</tr>
<tr>
<td>18. Banking</td>
<td>0.078</td>
<td>(0.093)</td>
<td>-0.094</td>
<td>(0.069)</td>
</tr>
<tr>
<td>19. Insurance</td>
<td>0.386**</td>
<td>(0.110)</td>
<td>0.163*</td>
<td>(0.081)</td>
</tr>
<tr>
<td>20. Personal services</td>
<td>-0.524**</td>
<td>(0.093)</td>
<td>-0.323**</td>
<td>(0.067)</td>
</tr>
<tr>
<td>21. Entertainment</td>
<td>0.237**</td>
<td>(0.087)</td>
<td>-0.016</td>
<td>(0.064)</td>
</tr>
<tr>
<td>22. Health services</td>
<td>0.037</td>
<td>(0.091)</td>
<td>-0.112</td>
<td>(0.066)</td>
</tr>
<tr>
<td>23. Legal and business services</td>
<td>0.277*</td>
<td>(0.108)</td>
<td>0.064</td>
<td>(0.079)</td>
</tr>
<tr>
<td>24. Non-profit organizations and private households</td>
<td>0.092</td>
<td>(0.093)</td>
<td>-0.061</td>
<td>(0.068)</td>
</tr>
<tr>
<td>25. Local collective organizations</td>
<td>0.023</td>
<td>(0.077)</td>
<td>-0.047</td>
<td>(0.057)</td>
</tr>
<tr>
<td>26. Social security</td>
<td>0.095</td>
<td>(0.121)</td>
<td>-0.059</td>
<td>(0.089)</td>
</tr>
</tbody>
</table>

Weighted adjusted standard deviation of differentials\(^b\) 0.146 0.072

F-statistic for no industry effect 9.768** 5.618**
\(\bar{R}^2\) 0.100 0.515
Sample size 2.072 2.072

\(^a\) Controls include age and its square, tenure and its square, five German education dummies, five foreign education dummies, nine skill dummies, four marital status dummies, a measure of health conditions, degree of satisfaction, and three firm-size dummies.

\(^b\) Weights are employment shares for each industry.

\(^*\) Statistically different from 0 at the 5% significance level.

\(^**\) Statistically different from 0 at the 1% significance level. The F test that all industry coefficients jointly equal 0 rejects at the 1% level. The 1% critical points are \(F_u (26, 2044) = 1.735\) for the regression without control variables and \(F_u (26, 2012) = 1.735\) for the regression with controls variables. The number of restrictions (degrees of freedom for the numerator) refers to the coefficients of 25 industry dummy variables and the coefficient of a dummy variable for missing industry affiliation.
mean differential: that is, I calculate the employment-weighted average of wage differentials for all industries as they result from the wage regression - which are the differentials relative to the excluded industry (agriculture), i.e. the coefficients of the industry dummy variables -, treating the omitted industry variable as having zero effect on wages; and then I report the difference between the industry dummies coefficients and this weighted average differential. The expression for wage differentials in deviation form is hence:

\[ D_k^* = \delta_k - \frac{L_{-1} \sum n_j \delta_j}{\sum n_j}, \quad k = 1, ..., K, \]  

(4.5)

where \( \delta_{kj} \) is the estimated coefficient of the dummy variable for industry \( k, j = 1, ..., K \) and \( n_j \) is employment in industry \( j = 1, ..., K \).

The normalization in deviation form of wage differentials presents a double advantage. First, this transformation makes the differentials totally independent of the arbitrarily chosen base sector (agriculture, in my case). Second, it provides a measure of wage differences which has a more useful and direct interpretation in economic terms. The resulting statistics represent in fact the proportionate difference in wages between an employee in a given industry and the average employee in the whole economy. These aspects of the normalization of differentials in deviation form are fully explained and proved in the general Appendix to the thesis.

Despite this transformation of wage differentials in deviation form, the standard errors appearing in Table 4.1 are simply the unadjusted OLS standard errors resulting from the estimate of the wage equation (4.1') in the second stage of my sample selection model (see Tables 4.B2 and 4.B3 in Appendix 4.B). Standard errors directly referring to differentials in deviation form can indeed be calculated from the OLS standard errors of the industry dummies coefficients of the wage equation, since each differential in deviation form is a linear combination of all industry dummy coefficients. The relevant formula is the following:
where I ignore the terms involving covariances \( \text{cov}(\hat{\delta}_k, \hat{\delta}_j) \), for \( k \neq j \), since experimentation with the 1984 SOEP data shows that accounting for these terms alters the estimated standard deviation by quantities only of order \( 10^{-3} \) or smaller. An unbiased estimate of this standard deviation is obtained using OLS variances (corrected for sample selection bias) as estimators of \( \text{var}(\hat{\delta}_k) \). The standard error for the wage differential of industry \( K \) (the excluded industry, agriculture) is not calculated, since an estimate for \( \text{var}(\hat{\delta}_K) \) is not available from the wage equation. However, the difference between \( \hat{\delta}_K \), the unadjusted OLS standard error of \( \hat{\delta}_K \), and the standard error derived from (4.6) is, in each case, only of order \( 10^{-3} \) or smaller. Therefore in Table 4.1 I present the values of the unadjusted OLS standard errors, since this does not affect my conclusions about the significance of individual industry differentials in deviation form. The same convention has been used by Krueger and Summers (1988)\(^{32}\). The reasons for this particular result and the conditions under which it may be obtained are fully illustrated in the general Appendix to the thesis. It essentially depends on the correct specification of the wage model and on the level of aggregation chosen in the classification of industry sectors. The Appendix also explains why these conditions are likely to hold also in Krueger and Summers's case, so that their procedure may be equally correct.

Again following Krueger and Summers (1988), to summarize the overall variability in industry wages I present the employment-weighted adjusted standard deviation of the industry wage differentials. The adjustment is required because the estimated industry wage differentials include a least squares sampling error, which leads to an upward bias in the

\[
SD \left( \hat{\delta}_k = \frac{\sum_{i=1}^{K} n_j \hat{\delta}_j}{\sum_{j=1}^{K} n_j} \right) = \sqrt{\left( 1 - \frac{2n_k}{\sum_{j=1}^{K} n_j} \right) \text{var}(\hat{\delta}_k) + \sum_{j=1}^{K} \left( \frac{\sum_{i=1}^{K} n_j^2 \text{var}(\hat{\delta}_j)}{\left( \sum_{j=1}^{K} n_j \right)^2} \right)^2}, \quad k = 1, ..., K-1, \quad (4.6)
\]

\(^{32}\) "The standard errors we report, however, are the unadjusted OLS standard errors." (Krueger and Summers, 1988, p.263, footnote 4)
standard deviation of wage differentials (Krueger and Summers, 1988, p.267). The standard
deviation is adjusted using the formula:

\[
SD(\delta) = \sqrt{\text{var}(\hat{\delta}) - \frac{1}{K-1} \sum_{k=1}^{K-1} \hat{\delta}_k^2},
\]

where \( \hat{\delta}_k \) is the OLS standard error of \( \hat{\delta}_k \). Like Krueger and Summers, I neglect the
covariance terms, which, as we have seen above, are extremely small. The differential \( \delta_J \) and
its standard error \( \hat{\delta}_J \) for agriculture, the omitted industry in the set of industry dummy
variables of the wage equation (4.1'), are again ignored in the calculation of the adjusted
standard deviation (4.7) since \( \hat{\delta}_J \) is not directly estimated, but just obtained as zero minus the
employment-weighted mean differential, and its standard error not available.

The results presented in Table 4.1 are obtained using as weights employment shares
by industry derived from national census statistics for the whole economy (Statistisches
Bundesamt, 1984). I also tried as weights employment shares by industry as resulting from
within the sample used for my regression analysis. With these two sets of weights, I obtained
only minor differences in the levels of industry wage differentials as deviations from the
employment-weighted mean differential\(^{33}\) and nearly identical employment-weighted adjusted
standard deviations of industry wage differentials\(^{34}\). This seems to confirm that the sample
used in the present study is representative of the underlying population in terms of distribution
of employees across industries.

---

\(^{33}\) For the differentials without controls of the first column, the use of sample employment shares as weights
gives wage differentials that exceed those obtained with population employment shares by 0.007; for the
differentials with controls of the third column, the use of population employment shares gives wage differentials
that exceed those obtained with sample employment shares by 0.010.

\(^{34}\) For the differentials without controls of the first column, the use of population and sample employment
shares as weights gives employment-weighted adjusted standard deviations equal to 0.146 and 0.147 respectively;
for the differentials with controls of the third column, the employment-weighted adjusted standard deviations are
0.072 and 0.075 respectively.
The first column of Table 4.1 presents raw industry wage differentials as deviations from the employment-weighted mean differential, that is industry wage differentials estimated without controlling for human capital, demographic and working conditions. The industry dummy coefficients in the wage equation are jointly statistically significant (the appropriate \( F \)-statistic is 9.768, significant at the 1% level since the 1% critical point is \( F_{0.01} (26, 2044) = 1.755 \)). Industry differentials in deviation form, however, are statistically significant individually in only 5 of the 26 cases at the 5% level and in 3 cases also at the 1% level. Estimates of the industry wage differentials range from -52 percent in the personal services sector, to +39 percent in the insurance sector. The employment-weighted adjusted standard deviation of raw industry wage differentials is 14.6 percent. This result is consistent with the findings of Krueger and Summers (1987, p.28, Table 2.4), where inter-country comparisons based on industry aggregate data show for Germany a standard deviation of log average earnings of 14.1 percent in 1982\(^{35}\).

The third column of Table 4.1 presents estimated industry wage differentials in deviation form when control variables for human capital and working conditions are introduced in the wage equation (see Appendix 4.B, Table 4.B3 for the parameter estimates of the control variables in the wage regression). With respect to raw industry differentials, 18 of the 26 differentials decrease in absolute size, with a mean relative reduction of about 49%; however, the other 8 differentials exhibit a considerable increase in absolute size, so that the overall mean relative change due to the introduction of controls is a growth of differentials of about 20%. In 14 of the 26 cases the differentials change in sign, but none of these remain significant in the wage regression with the controls. Estimates of industry differentials range from -32 percent in the personal services sector, to +16 percent in the insurance sector, the same sectors as in the case of raw differentials. It seems therefore that the addition of controls alters to a certain extent the pattern of wage differences. Industry differentials in deviation form are statistically significant in only 2 out of 26 industries at the 5% level and in 1 case

\(^{35}\) Krueger and Summers (1987, p.28, Table 2.4) provide the standard deviation of log average earnings among 24 manufacturing industries computed with aggregate annual data by industry. The earnings measure is earnings per hour, where earnings include wages and all wage supplements. Data are derived from ILO (1983). Their standard deviation of log earnings based on aggregate data - as a measure of wage dispersion - is comparable with my employment-weighted adjusted standard deviation of raw earnings differentials estimated in a regression based on individual data, where the dependent variable is log hourly earnings and the set of regressors includes only industry dummies (see Section 3.5 in Chapter 3).
also at the 1% level. Industry dummy coefficients in the wage equation remain nevertheless jointly significant at the 1% level (the appropriate \(F\)-statistic is 5.618, whereas the 1\% critical point is \(F_{0.01}(26, 2012) = 1.755\)). Controlling for worker characteristics also reduces substantially the estimated inter-industry wage dispersion. The employment-weighted adjusted standard deviation of industry wage differentials falls to 7.2 percent.

We can observe that, differently from the U.S. case illustrated by Krueger and Summers (1987 and 1988), raw industry wage differentials are not a very satisfactory approximation of the differentials obtained when control variables are introduced. This can be seen in Figure 4.1, where the plot of wage differentials estimated with controls against wage differentials estimated without controls does not show a very strong positive linear relationship. We can also evaluate the degree of stability of industry differentials to the introduction of controls by calculating the Pearson and Spearman correlations between differentials estimated without and with control variables in the wage equation. The motivation to use these two measures of association has already been illustrated in Chapter 3. The Pearson product-moment correlation provides a measure of the degree of (linear) stability which relies on the exact size of wage differentials and, therefore, is highly sensitive to extreme values. The Spearman rank correlation is less sensitive to extreme values and measures whether high- and low-wage industries tend to be the same before and after the introduction of controls, an aspect of stability of wage differentials which is of particular interest in the present context. Since both correlations are calculated for differentials in deviation form, they are independent of the particular industry chosen as a base (omitted) in the wage equation. The Pearson correlation between the estimated wage differentials in the first and third column of Table 4.1 - the measure used by Krueger and Summers (1987) to claim a strong stability of the pattern of industry wages with respect to controls in the U.S.\(^{36}\) - is 0.74, significantly different from zero at the 0.01% level\(^{37}\). This value is considerably smaller than that obtained by Krueger and Summers (1987) for the U.S., 0.95. Moreover, the

\(^{36}\) "It is clear that the addition of these controls barely alters the ranking of industry wage differences. Indeed the correlation of the industry wage differentials estimated with and without controls is 0.95." (Krueger and Summers, 1987, p.19). I have verified that this correlation is significantly different from zero at the 0.005% level.

\(^{37}\) This test of significance of the Pearson correlation for Germany and the one mentioned in the previous footnote for the U.S. are both based on the \(t\)-transformation suggested by Kendall and Stuart (1977) and presented in Chapter 3.
FIGURE 4.1
Estimated industry wage differentials with and without controls:
Germany, 1984
result is not confirmed by the value of the Spearman correlation between rankings of industry wage differences. For the German case, the rank correlation of the differentials estimated with and without controls is 0.50, which is not significantly different from zero at the 1% level\textsuperscript{38}. Differences in observed labour quality and working conditions seem to explain a considerable part of the variability of wages among industries. When human capital and working conditions controls are introduced in the wage regression, the standard error of the regression is reduced by 30 percent (from 0.338 to 0.237), the adjusted R\textsuperscript{2} increases from 10 percent to 52 percent and the employment-weighted adjusted standard deviation of differentials is reduced from 15 to 7 percent.

The general conclusion seems to be that although the size, significance, and dispersion of inter-industry wage differentials may cast some doubts on the standard competitive model of the labour market, human capital and working conditions factors play a crucial role in explaining the observed wage structure in Germany.

Two important caveats should be also taken into account in evaluating my findings. On the one hand, estimated industry differentials may appear smaller than the true differentials of non-competitive nature because of the inclusion of firm size variables among the controls in the wage equation. Both efficiency wage and insider-outsider theories, in fact, predict a positive relationship between firm size and wages: in the context of the efficiency wage model, turnover and monitoring costs may be higher in larger than in smaller firms and thus the efficiency wage may increase with firm size (Salop, 1973); in the context of the insider-outsider model, labour is expected to be better organized in large firms and thus insiders may be able to obtain a larger profit share (Weiss, 1966). There is some evidence for Germany supporting non-competitive explanations of the observed firm size-wage effect (Schmidt and Zimmermann, 1990). Whatever the underlying theoretical reason, firm size variables may "pick-up" some aspects of a non-competitive process of wage determination and therefore reduce the estimated industry affiliation effect.

On the other hand, estimated industry differentials may appear larger than the true differentials of non-competitive nature because of unobservable labour characteristics. In an

\textsuperscript{38} Using the results by Krueger and Summers (1987, Table 2.1), I computed the Spearman rank correlation for the U.S. case. This is also equal to 0.95, significantly different from zero at the 0.1% level. The claim of no impact of controls on the pattern of industry wages is therefore more justifiable in the U.S. case. Both tests of statistical significance of Spearman correlations are based on Zar's distribution table (Zar, 1972), described in Chapter 3.
approach based on the estimate of an earnings function like equation (4.1'). Unobservable characteristics which vary systematically across industries may produce upward biased estimates of the coefficients of the industry dummy variables, thus overstating the actual importance of industry affiliation in explaining the structure of wages. This problem seems even more serious in the German case than in the U.S. case, since here observable characteristics do have a substantial impact on relative wages. Inter-country comparisons of the sort presented in Chapter 3 to claim stability of the wage structure rely on the hypothesis that average wage differentials as emerging from aggregate data are a good approximation of the wage differentials that would result when all compensating differentials for labour quality and working conditions are controlled for. As I have already mentioned, there is some evidence supporting this hypothesis for the U.S. case. This leads Krueger and Summers (1987) to conclude,

"The finding (...) allows for the comparison of industry wages over time and across countries with aggregate industry wage data since it is unlikely that controls would change the pattern of industry wages in these data." (Krueger and Summers, 1987, p.20).

However, as we have seen in the present section, this hypothesis does not seem a realistic one for the German case. Even in an approach that cannot exclude compensating differentials for unobservable human capital characteristics and working conditions, observable labour quality controls explain a large amount of the variability of wages across industries and modify the pattern of inter-industry wage differentials.

In the following section, I will therefore consider inter-country comparisons based on results obtained with micro data and contrast the emerging conclusions with those drawn from evidence based on aggregate industry wage data.

Krueger and Summers (1987) find for the U.S. case that controlling for observable characteristics of workers does not change the pattern of wage differences and argue: "Unless unmeasured aspects of labor quality are only weakly correlated with tenure, age and education, and are far more important than measurable aspects, it is hard to see how they could account for inter-industry wage differences." (Krueger and Summers, 1987, p.38).
4.4 Comparisons with Evidence for the U.S., Australia, Austria and Sweden, Based on Micro Data

In this Section I will compare my results based on micro data for Germany with those of analogous works for the U.S. (Krueger and Summers, 1987, 1988), Australia (Borland and Suen, 1990), Austria (Winter-Ebmer, 1992) and Sweden (Edin and Zetterberg, 1989, 1992). When moving from aggregate to individual level data, we will see that differences between countries, rather than similarities, tend to emerge.

The five empirical studies use a similar approach: a wage equation - the logarithm of usual hourly earnings as a function of controls for human capital and working conditions and of industry dummies - estimated from a cross-sectional regression on individual data for one year in the period 1983-86. However, the degree of comparability between countries is affected by several differences in the definition of the samples of interest and of the dependent and explanatory variables, as well as in the statistical methodology applied for the estimate of the model.

The U.S. data are derived from the Current Population Survey (CPS), collected by the Bureau of Census for May 1984. CPS contains labour force data for members of the sampled households who are 14 years old or older. The sub-sample used by Krueger and Summers (1987, 1988) in their regression analyses consists of full- and part-time private non-agricultural employees 16 years old or older. Both male and female workers are included. Employees who report hourly earnings smaller than 1 US$ or greater than 250 US$ are considered to be outliers and eliminated from the sample. The authors obtain in this way a sub-sample of 11,512 individuals for the estimates of industry differentials with controls (Krueger and Summers, 1988) and a sub-sample of 10,289 individuals for the estimates of raw industry differentials without controls (Krueger and Summers, 1987) from a nationwide representative sample. The dependent earnings variable is defined as usual weekly earnings in the relevant month (May 1984) divided by usual weekly hours of work in the same time period. The set of explanatory variables used in the wage equation with controls (Krueger and Summers, 1988) includes: education and its square, 6 age dummies, 8 occupation dummies, 3 region dummies, sex, race, central city, union membership, marital status, veteran status dummies, several interaction terms. A set of 41 industry dummy variables is included in the
wage regressions both without and with controls. Wage equations are estimated with the OLS method.

The cross-sectional data-set which constitutes the basis for Borland and Suen’s (1990) study for Australia is the 1986 Australian Income Distribution Survey. This survey is derived from a multi-stage area sample of private dwellings and a sample of non-private dwellings. The survey also contains information at the individual level. Its coverage is approximately one-sixth of 1% of the population of Australia. The sub-sample analyzed by the authors contains full-time employees whose primary source of income is from wages and salaries. Attention is limited to male workers only, to avoid the problem of self selection involved in female labour participation. Employees earning less than 1 Aus$ per hour or more than 250 Aus$ per hour are regarded as outliers and eliminated from the sample. The resulting sub-sample of 4,574 individuals is then used to estimated a wage equation with control variables (estimates of raw industry differentials without controls are not presented). The dependent earnings variable is (current) usual weekly earnings from wages and salaries divided by usual weekly hours. The hours of work variable is coded into class intervals in the original survey data, so the authors adopt a conversion method to generate a continuous variable. The midpoint of a class interval is chosen as the value of this variable and for the upper interval \( \text{hours} \geq 40 \), 45 hours is chosen. The set of controls included in the wage equation is: 7 dummy variables for the highest educational qualification, experience and its square (age minus years of schooling minus 5, where years of schooling are obtained converting the information on educational qualifications), a range of schooling/experience (both in years) interaction terms, 6 state-of-residence dummies, 8 occupational dummies, 7 country-of-birth dummies, 2 marital status dummies and a dummy for participation in a superannuation scheme. A set of 11 industry dummies is also included among the explanatory variables. The wage equation is estimated with the OLS method.

Winter-Ebmer (1992), for his analysis of the Austrian case, uses a data-set of individual observations derived from the Austrian Mikrozensus 1983. The sub-sample considered is restricted to individuals between the ages of 19 and 55, with known industry affiliation. Both male and female workers are included in the sub-sample. The various selections lead to a sub-sample of 11,829 individuals, which is employed for the estimate of a wage equation with control variables. The author also estimates a wage equation without controls, but the results for industry wage differentials in this case are not presented in the
paper. The dependent variable is a measure of the hourly net wage, but no details are provided about the exact construction of this variable. The set of explanatory variables used in the wage equation includes: years of schooling and its square, completed apprenticeship, experience and its square, marital status, all for men and women separately (through variable×sex-dummy interaction terms); city size, regional dummies, nationality. 16 dummies for occupational status, gender dummy and weekly working time. A set of 24 industry dummies is included to evaluate the effect of industry affiliation. The wage equation is estimated using Heckman's two-stage method, to control for participation effects for both male and female workers. Identification of the participation selection function is achieved by various information on partners of the individuals in the sample (Winter-Ebmer, 1992, p.7. footnote 5).

Data for Sweden are obtained by Edin and Zetterberg (1989, 1992) from the Household Market and Nonmarket Activities (HUS) survey for 1984, which contains labour force and work place related data for members of about 1,500 households. A sub-sample is selected for full- and part-time employees in public and private sectors. Both male and female workers are included in the sub-sample considered for the latter article (Edin and Zetterberg, 1992), while the former paper (Edin and Zetterberg, 1989) also presented results for the two separate samples of either male or female workers. Observations with missing values in any of the dependent or explanatory variables are eliminated from the sample. A sub-sample of 1,298 male and female individuals (Edin and Zetterberg, 1992) and two further sub-samples of 671 male and 627 female individuals (Edin and Zetterberg, 1989) are thus obtained from a nationwide representative sample. The dependent variable is the log of the hourly wage rate, calculated as usual weekly (or other time units) earnings divided by usual hours of work for the corresponding time unit. The set of explanatory variables used in the wage equation with controls includes: education (years of schooling), experience and its square, tenure, age, sex, white-collar, native language not Swedish dummies, plant size, logarithm of regional unemployment rate, 6 shift dummies (3-shift, 2-shift, working weekends, working nights, irregular shifts, other shifts), 4 wage-form dummies (individual/group/mixed piece-rates, other piece-rates). A set of 26 industry dummy variables is included in the wage regressions both without and with controls. Wage equations are estimated with the OLS method.

These authors do not provide very detailed information about the procedures of sub-sample selection and the construction of their dependent variable. In particular, with the
exception of Winter-Ebmer (1992) for Austria, they do not specify anything about the
treatment of overtime workers or any other possibly endogenous selection criterion and ignore
the potential consequences in terms of selection bias. Although I am unable to reject the null
hypothesis of no sample selection effects with respect to the exclusion of overtime workers
from the unrestricted wage equation for Germany, this does not necessarily imply that no such
effects are present in other countries. Moreover, in the case of the U.S. and Sweden, the
choice of including both male and female employees in the selected samples and a dummy
variable for sex among the control variables - without correcting for endogenous self selection
- does not seem particularly appropriate, because it neglects the serious problem of self
selection connected with female labour supply.

With respect to the sets of control variables, we can observe some major differences
among the various studies. Differently from all the others (included my analysis of the
German case), the U.S. study includes among the controls a dummy variable for union
membership, but excludes any control for working conditions. Union membership is likely
to "pick-up" non-competitive influences on industry wages, thus reducing the size of the
estimated industry affiliation effect. On the other hand, the lack of controls for working
conditions may lead to upward biased estimates of the industry effect, due to the possible
existence of compensating wage differentials of a competitive nature. The analyses of the
Australian and Austrian cases essentially ignore any control for working conditions too (the
Austrian study includes only a variable for "weekly working time", of a rather obscure
nature). On the contrary, the Swedish case takes into account quite a rich set of working
conditions and work-place related controls, likely to "pick-up" both competitive and
non-competitive aspects of the process of wage determination. Furthermore, the analyses for
the U.S., Austria and Sweden specify the education variable in terms of years of schooling,
rather than a set of dummies for educational qualifications as in the cases of Australia and
Germany. As we have seen in Chapter 2 and previously in this Chapter, the former may not
be the most suitable choice, especially if part-time education has an important role in these
particular countries (Psacharopoulos and Layard, 1979). Other differences in the sets of
control variables mainly reflect peculiar institutional conditions characterizing the labour
markets of the five countries.

Finally, as already noticed, no treatment for potential sample selection bias is
contemplated in the U.S., Australian and Swedish studies: the simple OLS method is used to
provide estimates for the wage regressions on the selected samples. The use of a sample of male individuals only and of Heckman's correction on the sub-sample of straight-time workers in my analysis of the German case may represent a critical limitation to the comparability of my results especially with those from the U.S., for which a separate estimate of industry differentials for males is not available. In order to improve the reliability of comparisons, I have therefore also estimated industry differentials for Germany using a sample of both male and female workers, including a gender dummy among the explanatory variables and applying the simple OLS method. The original results of this second estimate are presented in Appendix 4.C. Table 4.C2, in terms of 22 industry wage differentials in deviation form estimated without and with controls. Aggregations of these initial estimates will also be used in comparisons with countries other than the U.S. In all the pair-wise cross-country comparisons that will follow, I will use either one or the other set of results for Germany, according to which represents the most appropriate choice given the characteristics of the analysis for the other country involved in the comparison. Details about the estimates actually used are presented in each table of Appendix 4.C.

Taking into proper account the limits to the degree of comparability arising from all these differences, I will proceed with cross-country comparisons considering some aspects of the empirical evidence available from the different studies. The estimates of raw industry differentials without controls for the U.S., Germany and Sweden are summarized in Table 4.2 (raw differentials are not available for Australia and Austria), while Table 4.3 presents industry wage differentials estimated with controls for human capital and working conditions for all five countries. Differentials are expressed as deviations from the employment-weighted mean differential for all countries, so that the base industry excluded from the wage equation - which varies across studies and sometimes is even unknown - becomes irrelevant (see Section 4.3). The results for Germany are derived in this case from OLS estimates on the sample of both male and female workers. The values appearing in Tables 4.2 and 4.3 are then graphed in Figures 4.2 and 4.3 respectively.

A further limit in the actual comparison is represented by differences in the industry classifications used in the original studies for the five countries. I can therefore consider only the most detailed possible common classification, even if this entails a considerable loss of information with respect to the initial results. The common set of industries contains in fact only 10 sectors, while the original differentials where estimated for much larger, more
### TABLE 4.2

Estimated wage differentials without controls for human capital and working conditions for the U.S., Germany and Sweden: deviations from the employment-weighted mean differential

<table>
<thead>
<tr>
<th>Industry</th>
<th>U.S. 1984*</th>
<th>Germany 1984*</th>
<th>Sweden 1984*</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Agriculture</td>
<td>—</td>
<td>-0.204</td>
<td>-0.149</td>
</tr>
<tr>
<td>2. Mining, public utilities</td>
<td>0.479</td>
<td>0.209</td>
<td>0.031</td>
</tr>
<tr>
<td>3. Manufacturing</td>
<td>0.174</td>
<td>0.028</td>
<td>0.015</td>
</tr>
<tr>
<td>4. Construction</td>
<td>0.216</td>
<td>0.086</td>
<td>0.066</td>
</tr>
<tr>
<td>5. Trade</td>
<td>-0.223</td>
<td>-0.186</td>
<td>-0.030</td>
</tr>
<tr>
<td>6. Transport, communications</td>
<td>0.294</td>
<td>0.036</td>
<td>0.013</td>
</tr>
<tr>
<td>7. Finance, business services</td>
<td>0.062</td>
<td>0.123</td>
<td>0.151</td>
</tr>
<tr>
<td>8. Personal services</td>
<td>-0.397</td>
<td>-0.086</td>
<td>-0.108</td>
</tr>
<tr>
<td>9. Social services</td>
<td>0.003</td>
<td>-0.021</td>
<td>-0.024</td>
</tr>
<tr>
<td>10. Public administration</td>
<td>—</td>
<td>0.047</td>
<td>0.048</td>
</tr>
</tbody>
</table>

Mean differential               | 0.076      | 0.003         | 0.001        |
Mean differential in absolute size | 0.231      | 0.103         | 0.063        |
Weighted standard deviation of differentials | 0.264      | 0.124         | 0.081        |
Sample size<sup>d</sup>          | 10.289     | 4.389         | 1.298        |


<sup>b</sup> Sample employment-weighted aggregations of the original differentials presented in Table 4.C2, Appendix 4.C. Original estimation method: OLS.


<sup>d</sup> For all three countries, the samples considered include male and female workers.
<table>
<thead>
<tr>
<th>Industry</th>
<th>U.S. 1984*</th>
<th>Australia 1986*</th>
<th>Germany 1984*</th>
<th>Austria 1983*</th>
<th>Sweden 1984*</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Agriculture</td>
<td>-</td>
<td>-0.291</td>
<td>-0.105</td>
<td>-0.106</td>
<td>-0.061</td>
</tr>
<tr>
<td>2. Mining, public utilities</td>
<td>0.252</td>
<td>0.280</td>
<td>0.092</td>
<td>0.073</td>
<td>0.010</td>
</tr>
<tr>
<td>3. Manufacturing</td>
<td>0.105</td>
<td>0.028</td>
<td>0.022</td>
<td>-0.005</td>
<td>0.016</td>
</tr>
<tr>
<td>4. Construction</td>
<td>0.126</td>
<td>0.035</td>
<td>0.070</td>
<td>0.043</td>
<td>0.069</td>
</tr>
<tr>
<td>5. Trade</td>
<td>-0.124</td>
<td>-0.057</td>
<td>-0.076</td>
<td>-0.030</td>
<td>-0.015</td>
</tr>
<tr>
<td>6. Transport, communications</td>
<td>0.145</td>
<td>0.079</td>
<td>-0.019</td>
<td>-0.032</td>
<td>0.008</td>
</tr>
<tr>
<td>7. Finance, business services</td>
<td>0.030</td>
<td>0.031</td>
<td>0.014</td>
<td>0.021</td>
<td>0.075</td>
</tr>
<tr>
<td>8. Personal services</td>
<td>-0.199</td>
<td>-0.093</td>
<td>-0.031</td>
<td>-0.010</td>
<td>-0.048</td>
</tr>
<tr>
<td>9. Social services</td>
<td>-0.083</td>
<td>-0.009</td>
<td>-0.032</td>
<td>0.040</td>
<td>-0.030</td>
</tr>
<tr>
<td>10. Public administration</td>
<td>-</td>
<td>0.063</td>
<td>-0.021</td>
<td>-0.027</td>
<td>0.028</td>
</tr>
</tbody>
</table>

Mean differential          | 0.032      | 0.007           | -0.009        | -0.003        | 0.005        |
Mean differential in absolute size | 0.133 | 0.097           | 0.048         | 0.039         | 0.036        |
Weighted standard deviation of differentials | 0.144 | 0.137           | 0.057         | 0.048         | 0.043        |
Sample size                | 11,512     | 4,574           | 4,389         | 11,829        | 1,298        |


c Sample employment-weighted aggregations of the original differentials presented in Table 4.C2, Appendix 4.C. Original estimation method: OLS.


f For the U.S., Germany, Austria and Sweden, the samples considered include male and female workers; for Australia, the sample consists only of male workers.
FIGURE 4.2

Industry wage differentials estimated without controls

*For the United States, agriculture and public administration not available.

FIGURE 4.3

Industry wage differentials estimated with controls

*For the United States, agriculture and public administration not available.
disaggregate sets of industries. Originally estimated differentials are aggregated into these 10 sectors by calculating employment-weighted averages of differentials. In this procedure it would be appropriate to use as weights sample employment shares by industry as they emerge from the sub-samples used in the various econometric analyses. Sample-employment-weighted averages of differentials are in fact exactly the same as the differentials that one would obtained from directly estimating a regression of log wages on the corresponding more aggregate set of industry dummies\textsuperscript{40}. I therefore use sample employment shares whenever possible. However, for the U.S. and Sweden sample employment shares are not available from the respective studies, so population employment shares are used as weights instead (U.S. Department of Labor, 1989, pp.96-99, Table 19; Nordic Statistical Secretariat, 1985, pp.96-97. Table 52; Statistiska Centralbyrån, 1989, pp.91-94, Table 7.3). Details on the level and method of aggregation applied in each case are also reported in the various tables of Appendix 4.C.

A first relevant difference among the five countries is the magnitude of industry wage differentials. Empirical evidence shows the existence of a ranking of countries both in terms of their mean differential in absolute size and in terms of single differentials in the majority of industries. The ordering of countries, from the one with the largest to the one with the smallest differentials, is the following: U.S., Australia, Germany, Austria, Sweden. This is true both for raw differentials and also when control variables are introduced in the wage equation.

The most striking difference among the five countries is in terms of the variability of wages across industries as measured by the employment-weighted standard deviation of industry differentials. For the raw differentials estimated without controls for human capital and working conditions, the U.S. (26 percent) present a greater variability than Germany (12 percent) and Germany a greater variability than Sweden (8 percent). Referring to the results obtained when large numbers of controls are added to the wage equations, the figures for the U.S., Australia, Germany, Austria and Sweden are, respectively, 14 percent, 14 percent, 6 percent, 5 percent and 4 percent. So, the same ranking of countries illustrated before tends to appear.

Differences emerge also in the comparison of the overall industry wage structures of the various countries. Figures 4.2 and 4.3 provide a first idea of the degree of stability of the

\textsuperscript{40} This result derives from the particular properties of dummy variable models (industry variables are binary dummies). See the Appendix to the thesis for a general illustration of these properties.
industry wage pattern across countries. Figure 4.2 presents plots of raw wage differentials estimated without controls in the U.S. Germany and Sweden, the three countries for which this type of results are available. Considerable dissimilarities among countries are evident. Figure 4.3 shows instead the plots of industry differentials obtained after controlling for human capital and working conditions in all countries. Differentials are generally reduced with respect to Figure 4.2, but dissimilarities persist. Only Germany, Austria and Sweden tend to become more similar, but only to a limited extent.

Further differences concern the statistical significance of industry differentials and the relative importance of human capital variables and industry variables in the wage equations. These aspects of the various results do not appear in Tables 4.2 and 4.3, since the two tables report only employment-weighted aggregations of the original estimates. I will therefore refer to specific findings presented in the original studies by the respective authors.

The five countries also differ in terms of statistical significance of individual industry differentials. For the U.S., industry differentials are generally statistically significant both when estimated without controls and when human capital and working conditions controls are introduced in the wage regression (Krueger and Summers, 1988). For Australia, 10 out of 11 differentials are statistically significant at the 5% level and 9 of these also at the 1% level in a wage equation which includes a large set of control variables (Borland and Suen, 1990). In my analysis of the German case presented in Section 4.3, 5 of the 25 industry differentials estimated without controls are statistically significant at the 5% level and 3 of these also at the 1% level. When control variables are introduced, only 2 differentials remain statistically significant, one at the 5% level only and the other also at the 1% level. For Austria, 10 of the 24 industry differentials estimated with controls are statistically significant at the 5% level and 7 of these also at the 1% level (Winter-Ebmer, 1992). For Sweden, 7 of the 26 industry differentials estimated without controls are statistically significant at the 5% level and 5 of them also at the 1% level. If a large number of control variables are introduced in the wage regression, only 3 differentials remain significant at the 5% level and only one of these also at the 1% level. In all countries, however, industry differentials are jointly statistically significant at the 1% level (Edin and Zetterberg, 1992).

It is worth noting that differences in the level of significance may simply reflect differences in the sample sizes. The standard error of least squares coefficients is in fact an increasing function of the inherent variability of the dependent variable and a decreasing
function of the sample size and of the variability of each explanatory variable. Thus, other things being equal, a larger sample size leads to more accurate estimates and higher significance levels. For example, the size of the sample considered here for the U.S. study (11,512) is about 6 times the sample size in my analysis of the German case (2,072) and about 9 times that of the Swedish study (1,298) and this seems to be reflected in the statistical significance of individual differentials in the three countries. However, the size of the sample for Austria (11,829) is even larger than that for the U.S., while results in terms of statistical significance are remarkably different with a much stronger significance of the U.S. differentials. And on the other hand, the U.S. sample size is about 2 ½ times the sample size for Australia, while statistical significance of individual differentials is equally very high in almost all industries.

A final difference is the relative importance of human capital variables and industry variables in the wage equations for the various countries. In the U.S., industry variables are rather important in explaining variations in individual wages. The standard error of the regression is reduced by 4.3 percent when industry variables are added to a regression that already controls for occupation, human capital, and demographic factors. In comparison, the standard error falls by 5.1 percent when human capital controls are added to an equation that already includes industry variables (Krueger and Summers, 1988). For Germany, when industry variables are introduced into a regression that already controls for a number of human capital and working conditions, the standard error of the regression is reduced by 3.9 percent, while when human capital controls are added to a regression that already includes industry variables the standard error falls by 4.5 percent (see Appendix 4.B, Tables 4.B2, 4.B3). A totally different outcome is instead obtained for Austria and Sweden. The results presented by Winter-Ebmer (1992) for Austria are in ANOVA terms, rather than standard errors of regressions. The addition of industry variables to a regression which already includes human capital controls increases the explanatory power of the wage equation (in terms of $R^2$) by 1.6 percent. On the other hand, the inclusion of control variables to a regression which already contains industry variables increases the explanatory power of the wage equation by 20.3 percent, almost 13 times the increase due to industry variables. For Sweden, the reduction in the standard error of the regression due to the introduction of industry variables in an equation that already controls for human capital and working conditions is 0.2 percent, while that due to the addition of control variables to an equation that already includes industry
variables is 2.2 percent, more than ten times the reduction due to industry variables. Similar results for Australia are unfortunately not available. This means that in the U.S. and in Germany industry variables and human capital controls are of nearly equal importance in accounting for wage variations, with Germany exhibiting a slightly smaller impact of industry variables than the U.S., while in Austria and Sweden human capital variables are relatively much more important, with industry variables having a very small effect on the estimated wage equation.

A more exact picture of the degree of similarity between industry wage structures across countries can be obtained by computing Pearson product-moment correlations and Spearman rank correlations for industry differentials in a series of pair-wise comparisons. The rationale for considering both correlations has been explained in Chapter 3 and earlier in Section 4.3. The values of the correlations for the five countries considered here are reported in Table 4.4, for differentials in deviation form estimated both without (when available) and with controls. The source of the original estimated differentials, the method of aggregation of differentials into a common classification of industries, and the final number of sectors actually involved in the correlations change for each pair of countries. This has been done in order to achieve the highest possible degree of comparability of results between countries, while preserving the level of accuracy contained in the original information as far as possible - i.e., defining the largest possible set of common sectors in each case. The vectors of differentials used in the various pair-wise comparisons and other details are presented in the tables of Appendix 4.C.

Table 4.4 shows that correlations are generally not very high. They are significantly greater than zero in 15 of the 26 cases at the 1% level and in only 10 cases also at the more rigorous 0.5% level, considered here in order to take into account the small size of the samples of differentials involved. They are also rather weak in several cases. Correlations generally tend to decrease when control variables are introduced in the wage equations, with the only exception of the Spearman correlation between the U.S. and Sweden. A strong degree of similarity after controlling for human capital and working conditions seems to exist only between the U.S. and Australia in terms of their Spearman correlation (0.976), but this result is not confirmed by the respective Pearson correlation, which is considerably lower (0.771). A certain degree of similarity between industry wage structures estimated with controls is found for Australia and Germany, in terms of both Pearson and Spearman


<table>
<thead>
<tr>
<th></th>
<th>Australia 1986</th>
<th>Germany 1984</th>
<th>Austria 1985</th>
<th>Sweden 1984</th>
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<tr>
<td><strong>U.S. 1984</strong></td>
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<td>Pearson:</td>
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<tr>
<td>with</td>
<td>0.563**</td>
<td>0.470</td>
<td>0.287</td>
<td>0.531**</td>
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<tr>
<td></td>
<td>(0.003)</td>
<td>(0.014)</td>
<td>(0.098)</td>
<td>(0.006)</td>
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<td>Spearman:</td>
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<tr>
<td>with</td>
<td>0.771**</td>
<td>0.585**</td>
<td>0.436</td>
<td>0.467</td>
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<td>(0.004)</td>
<td>(0.005)</td>
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<td><strong>Australia 1986</strong></td>
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<td>Pearson:</td>
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<tr>
<td>with</td>
<td>0.795**</td>
<td>0.738**</td>
<td>0.430</td>
<td>0.364</td>
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<tr>
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<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.082)</td>
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<td>with</td>
<td>0.782**</td>
<td>0.482</td>
<td>0.364</td>
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<td><strong>Germany 1984</strong></td>
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<td>Pearson:</td>
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<tr>
<td>with</td>
<td>0.788**</td>
<td>0.439</td>
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<td></td>
<td>(0.000)</td>
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<tr>
<td>Spearman:</td>
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<td>with</td>
<td>0.760**</td>
<td>0.542*</td>
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<td>(0.0005)</td>
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<td>(0.01)</td>
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<td><strong>Austria 1985</strong></td>
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<tr>
<td>with</td>
<td>0.418</td>
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<td>(0.030)</td>
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<tr>
<td>Spearman:</td>
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<tr>
<td>with</td>
<td>0.435</td>
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<tr>
<td></td>
<td>(0.025)</td>
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1. t-tailed tests of the null hypothesis $H_0: \rho, \rho_s = 0$, against the alternative hypothesis $H_1: \rho, \rho_s > 0$. The relevant claim is, in fact, that the international wage structure is stable across countries. Only positive correlations are therefore expected. The tests for Pearson correlations are based on the $t$-transformation suggested by Kendall and Stuart (1977, p. 416, §16.28). The tests for Spearman correlations are based on Zar’s distribution table (Zar, 1972, p. 579). See Chapter 3 for details.

4. Source: my results from the SOEP, presented in Section 4.3, Table 4.1, and in Appendix 4C, Table 4.C2.
7. Statistically significant at the 1% level.
8. Statistically significant at the 0.5% level.
correlations: Australia and Austria, in terms of Pearson correlation but not of Spearman correlation; Germany and Austria, in terms of both Pearson and Spearman correlations. Also, industry differentials in Germany and Austria appear rather different from those in Sweden. Therefore these results cannot be regarded as supportive of the existence of a North American versus a European pattern.

Without overvaluing the reliability of these comparisons, it is worth noting that we are very far from the results obtained by Krueger and Summers (1987) and Gittleman and Wolff (1993) with aggregate data and presented in Chapter 3. Krueger and Summers show Pearson correlations between log average industry wages in 1982 equal to 0.85 for the U.S. and Germany, 0.82 for the U.S. and Sweden, and 0.84 for Germany and Sweden (see Table 3.7 in Chapter 3). Gittleman and Wolff obtain Pearson correlations between aggregate wage differentials for all industries in 1985 equal to 0.82 for the U.S. and Australia, 0.86 for the U.S. and Germany, and 0.78 for the U.S. and Sweden (see Table 3.8 in Chapter 3). This indicates that the magnitude of correlations between countries may be overstated in aggregate data and that a substantial proportion of similarities may be due to the correlation of the industry distribution of observable and unobservable labour quality and job attributes across countries (Edin and Zetterberg, 1992).

Within the limits of the actual comparability of empirical evidence for the U.S., Australia, Germany, Austria and Sweden, the fact that differences between countries, rather than similarities, tend to emerge seems to suggest that institutional aspects of the labour market, and in particular the degree of centralization of wage bargaining, may play an important role in explaining the observed pattern of inter-industry wage differentials. The ranking of the five countries in terms of degree of centralization is consistent with the empirical results for industry wage differences estimated with individual data in the framework of human capital earnings functions. Union policies aiming at a reduction of wage differentials have been successful in Sweden and partly in Germany and Austria. On the other hand, the lack of centralized policies in wage negotiations appears to lead the U.S. and Australia towards a labour market characterized by wide inter-sectoral differentials. These findings are confirmed by additional evidence provided by Holmlund and Zetterberg (1991). Using panel data on aggregate industry wages for five countries including the U.S., Germany, and Sweden, they find that industry wages in the U.S. are substantially affected by industry specific conditions, while in Sweden these effects are negligible. Germany plays an
intermediate role, with substantial industry wage differentials but modest wage response to sectoral conditions.

4.5 Conclusions

The aims of this Chapter have been to present some empirical evidence of the inter-industry wage dispersion in Germany based on the SOEP micro data and to compare my results with those provided in four similar studies on the U.S., Australia, Austria and Sweden.

Evidence for Germany shows that workers' quality and other compensating factors have an important impact on the observed wage structure, although the size, significance, and dispersion of inter-industry wage differentials may cast some doubts on the standard competitive model of the labour market.

Comparisons with U.S., Australian, Austrian and Swedish evidence suggest that results obtained with individual data in a regression approach highlight differences among countries rather than similarities, in contrast to what emerges with aggregate data. Institutional conditions of wage bargaining and in particular the degree of centralization seem to play a relevant role in explaining the pattern of inter-industry wage differentials.

These conclusions are obviously affected by numerous discrepancies in the methodology used in the various studies by different authors. Heterogeneity in the sub-samples of selected individuals, the dependent and explanatory variables entering the wage models, the econometric techniques applied, and the classifications of industry sectors characterizing each study may represent a severe limit to the reliability of cross-country comparisons. In the next Chapter, I will therefore consider inter-country comparisons based on a different approach: a direct estimate of industry differentials for five countries based on the micro data-sets collected in the "Luxembourg Income Study" data-bank.
Appendix 4.A: SOEP, Wave 1 (1984) Variables Involved in the Selection of the Sub-Sample and in the Construction of the Model Variables

1) Sub-sample selection

*Table*  
**PPFAD**

Variable  
ANETTO = SURVEY STATUS FOR WAVE 1

-2 = PERSON NOT IN GROSS PANEL DATABASE
1 = SUCCESSFUL INDIVIDUAL INTERVIEW
2 = HAS NOT YET REACHED PANEL AGE
3 = DID NOT PARTICIPATE IN WAVE 1
4 = MISSING IN WAVE 1

Selected group: ANETTO = 1

Variable  
SEX = SEX

1 = MALE
2 = FEMALE
3 = NO DATA

Selected group: SEX = 1

Variable  
GEBJahr = BIRTH YEAR (4-digit)

Selected group: (1984 - GEBJAHR) ≤ 65

*Table*  
**AP**

Variable  
AP08 = PRESENT EMPLOYMENT STATUS

1 = FULL-TIME EMPLOYED
2 = REGULARLY PART-TIME EMPLOYED
3 = ENGAGED IN IN-COMPANY TRAINING
4 = MINIMALLY OR IRREGULARLY EMPLOYED
5 = REGISTERED AS UNEMPLOYED
6 = PERFORMING MILITARY/CIVILIAN SERVICE
7 = NOT EMPLOYED

Selected group: AP08 = 1,2

Variable AP2801 = OCCUPATIONAL STATUS: BLUE-COLLAR WORKERS

-2 = MISSING: NOT APPLICABLE
1 = UNSKILLED WORKER
2 = UNSKILLED WORKER WITH ON-THE-JOB TRAINING
3 = TRAINED WORKER
4 = FOREMAN
5 = MASTER

Selected groups: AP2801 = 1,2,3,4,5

Variable AP2804 = OCCUPATIONAL STATUS: WHITE-COLLAR WORKERS

-2 = MISSING: NOT APPLICABLE
1 = WHITE-COLLAR INDUSTRIAL WORKER
2 = WHITE-COLLAR WORKER IN BASIC POSITIONS
3 = WHITE-COLLAR WORKER WITH ADVANCED QUALIFICATIONS
4 = HIGHLY TRAINED WHITE-COLLAR WORKER
5 = WHITE-COLLAR WORKER WITH EXTENSIVE LEADERSHIP RESPONSIBILITIES

Selected groups: AP2804 = 1,2,3,4,5

Variable AP3002 = NO SCHEDULED WEEKLY HOURS OF WORK

-2 = MISSING: NOT APPLICABLE
-1 = MISSING: NOT AVAILABLE
1 = NO SCHEDULED WEEKLY HOURS OF WORK

Selected group: AP3002 = -2

Variable AP3301 = GROSS WAGES/SALARIES IN THE LAST MONTH

Selected group: AP3301 > 0

Variable AP3001 = SCHEDULED WEEKLY HOURS OF WORK, NOT INCLUDING OVERTIME

Selected group: AP3001 > 0
Variable \[ \text{WPERH} = \frac{\text{AP3301}}{4 \times \text{AP3001}} = \text{HOURLY WAGE/SALARY} \]

Selected group: \( \text{WPERH} > 1 \)

2) Construction of the overtime work binary dependent variable for the PROBIT equation

Table \( \text{AP} \)

Variables

- \( \text{AP3001} = \text{SCHEDULED WEEKLY HOURS OF WORK. NOT INCLUDING OVERTIME} \)
- \( \text{AP31} = \text{AVERAGE ACTUAL WEEKLY WORK HOURS. INCLUDING OVERTIME} \)
- \( \text{AP32} = \text{TYPE OF COMPENSATION FOR OVERTIME} \)

-2 = MISSING: NOT APPLICABLE
-1 = MISSING: NOT AVAILABLE
1 = PAY
2 = TIME OFF
3 = SOMETIMES PAY, SOMETIMES TIME OFF
4 = NO COMPENSATION AT ALL
5 = NO OVERTIME

 Constructed dummy: \( \text{OT: AP3001} \neq \text{AP31} \text{ AND AP32} \neq 4 \)

3) Construction of human capital, demographic, and working conditions controls

3.1) Age:

Table \( \text{PPFAD} \)

Variable \( \text{GEBJahr} = \text{BIRTH YEAR (4-digit)} \)

Constructed variables: \( \text{AGE} = 1984 - \text{GEBJahr} \)
\( \text{AGESQ} = (1984 - \text{GEBJahr})^2 \)
3.2) Tenure:

**Table AP**

Variables

AP2301 = YEAR HIRED BY PRESENT EMPLOYER (2-digit)

AP2302 = MONTH HIRED BY PRESENT EMPLOYER

Constructed variables:

TENURE = (84 - AP2301) + (12 - AP2302)/12

TENURESQ = ((84 - AP2301) + (12 - AP2302)/12)^2

3.3) Education:

**Table AP**

Variables

AP06 = HIGHEST SCHOOL GRADE COMPLETED

-2 = MISSING: NOT APPLICABLE

-1 = MISSING: NOT AVAILABLE

1 = SHORT-COURSE SECONDARY SCHOOL

2 = INTERMEDIATE TYPE OF SECONDARY SCHOOL

3 = TECHNICAL HIGH SCHOOL

4 = ACADEMICALLY-ORIENTED SECONDARY SCHOOL

5 = OTHER SCHOOL

6 = NONE OF THE ABOVE

AP0707 = TECHNICAL COLLEGE, ENGINEERING SCHOOL

-2 = MISSING: NOT APPLICABLE

1 = TECHNICAL COLLEGE, ENGINEERING SCHOOL

AP0708 = COLLEGE/UNIVERSITY

-2 = MISSING: NOT APPLICABLE

1 = COLLEGE/UNIVERSITY

**Table APAUSL**

Variables

AP06A01 = ATTENDED SCHOOL IN FRG

-1 = MISSING: NOT AVAILABLE
1 = YES
2 = NO

AP06A02 = GERMAN SCHOOL GRADE COMPLETED

-2 = MISSING: NOT APPLICABLE
-1 = MISSING: NOT AVAILABLE
1 = NO SCHOOLING
2 = SHORT-COURSE SECONDARY SCHOOL
3 = INTERMEDIATE TYPE OF SECONDARY SCHOOL
4 = TECHNICAL HIGH SCHOOL
5 = ACADEMICALLY-ORIENTED SECONDARY SCHOOL
6 = OTHER SCHOOL

AP06B01 = ATTENDED FOREIGN SCHOOL

-1 = MISSING: NOT AVAILABLE
1 = YES
2 = NO

AP06B02 = FOREIGN SCHOOL GRADE COMPLETED

-2 = MISSING: NOT APPLICABLE
-1 = MISSING: NOT AVAILABLE
1 = COMPULSORY SCHOOL WITHOUT FINAL EXAMINATION
2 = COMPULSORY SCHOOL WITH FINAL EXAMINATION
3 = FURTHER SCHOOLING

AP07A01 = TRAINING OR QUALIFICATION RECEIVED IN FRG

-1 = MISSING: NOT AVAILABLE
1 = YES
2 = NO

AP07A09 = TECHNICAL COLLEGE, ENGINEERING SCHOOL

-2 = MISSING: NOT APPLICABLE
1 = TECHNICAL COLLEGE, ENGINEERING SCHOOL

AP07A10 = COLLEGE/UNIVERSITY

-2 = MISSING: NOT APPLICABLE
1 = COLLEGE/UNIVERSITY

AP07B01 = TRAINING RECEIVED IN ANOTHER COUNTRY

-1 = MISSING: NOT AVAILABLE
1 = YES
2 = NO

**AP07B04 = SPECIALIZED PROFESSIONAL SCHOOL**

-2 = MISSING: NOT APPLICABLE
1 = SPECIALIZED PROFESSIONAL SCHOOL

**AP07B05 = COLLEGE/UNIVERSITY**

-2 = MISSING: NOT APPLICABLE
1 = COLLEGE/UNIVERSITY

**Constructed dummies:**

- **DGED1:** AP06 = 1,5,6 OR AP06A02 = 1,2,6
- **DGED2:** AP06 = 2 OR AP06A02 = 3
- **DGED3:** AP06 = 3,4 OR AP06A02 = 4,5
- **DGED4:** AP0707 = 1 OR AP07A09 = 1
- **DGED5:** AP0708 = 1 OR AP07A10 = 1
- **DFED0:** AP06A01 = 2 OR AP06B01 = 2 OR AP07A01 = 2 OR AP07B01 = 2 (base group)
- **DFED1:** AP06B02 = 1
- **DFED2:** AP06B02 = 2
- **DFED3:** AP06B02 = 3
- **DFED4:** AP07B04 = 1
- **DFED5:** AP07B05 = 1

### 3.4) Skill:

**Table AP**

**Variables**

**AP2801 = OCCUPATIONAL STATUS: BLUE-COLLAR WORKERS**

-2 = MISSING: NOT APPLICABLE (excluded)
1 = UNSKILLED WORKER
2 = UNSKILLED WORKER WITH ON-THE-JOB TRAINING
3 = TRAINED WORKER
4 = FOREMAN
5 = MASTER

**AP2804 = OCCUPATIONAL STATUS: WHITE-COLLAR WORKERS**

-2 = MISSING: NOT APPLICABLE (excluded)
1 = WHITE-COLLAR INDUSTRIAL WORKER
2 = WHITE-COLLAR WORKER IN BASIC POSITIONS
3 = WHITE-COLLAR WORKER WITH ADVANCED QUALIFICATIONS
4 = HIGHLY TRAINED WHITE-COLLAR WORKER

179
5 = WHITE-COLLAR WORKER WITH EXTENSIVE LEADERSHIP RESPONSIBILITIES

Constructed dummies:  
DSKILL1: AP2801 = 1 (base group)  
DSKILL2: AP2801 = 2  
DSKILL3: AP2801 = 3  
DSKILL4: AP2801 = 4  
DSKILL5: AP2801 = 5  
DSKILL6: AP2804 = 1  
DSKILL7: AP2804 = 2  
DSKILL8: AP2804 = 3  
DSKILL9: AP2804 = 4  
DSKILL10: AP2804 = 5

3.5) Marital status:

Table AP

Variable AP58 = MARITAL STATUS

-2 = MISSING: NOT APPLICABLE
-1 = MISSING: NOT AVAILABLE
1 = MARRIED, LIVING WITH SPOUSE
2 = MARRIED BUT PERMANENTLY SEPARATED
3 = SINGLE
4 = DIVORCED
5 = WIDOWED

Constructed dummies:  
DMARI1: AP58 = 1  
DMARI2: AP58 = 2  
DMARI3: AP58 = 3 (base group)  
DMARI4: AP58 = 4  
DMARI5: AP58 = 5

3.6) Nationality:

Table AP

Variable AP61 = CITIZENSHIP

-1 = MISSING: NOT AVAILABLE
1 = GERMANY
2 = TURKEY
3 = YUGOSLAVIA
4 = GREECE
5 = ITALY
6 = SPAIN
10 = AUSTRIA
11 = FRANCE
12 = BENELUX
14 = ENGLAND
17 = FINLAND
18 = USA
19 = SWISS
20 = CHILE
22 = POLAND
23 = KOREA
24 = IRAN
25 = INDONESIA
26 = HUNGARY
28 = PORTUGAL
29 = BULGARIA
31 = CZECHOSLOVAKIA
32 = USSR
34 = MEXICO
36 = GREEN CAPE
38 = PHILIPPINES
39 = ISRAEL
40 = JAPAN
41 = AUSTRALIA
42 = INDIA
43 = AFGHANISTAN
98 = NO CITIZENSHIP

Constructed dummies: DNAT1: AP61 = 1 (base group)
DNAT2: AP61 = 2
DNAT3: AP61 = 3
DNAT4: AP61 = 4
DNAT5: AP61 = 5
DNAT6: AP61 = 6,10,11,12,14,17,18,20,22,23,24,25,26,28,29,
31,32,34,36,38,39,40,41,42,43
DNATMIS: AP61 = -1,98

3.7) Number of children:

Table AKIND

Variable AKZAHL = NUMBER OF CHILDREN IN THE HOUSEHOLD
Variable AP66A02 = NUMBER OF CHILDREN OUTSIDE FRG

Constructed variable: NKIDS = AKZAHL + AP66A02

3.8) Second house:

Variable AP6001 = SECOND HOUSE IN FRG

-1 = MISSING: NOT AVAILABLE
1 = YES
2 = NO

Constructed dummy: DHOUSE2: AP6001 = 1

3.9) Mortgage:

Variable AH2601 = MONTHLY HOUSING COSTS FOR PRINCIPAL/INTEREST

Constructed dummy: DMORT: AH2601 > 0

3.10) Health conditions:

Variable AP5103 = NUMBER OF NIGHTS SPENT IN HOSPITAL IN PRIOR YEAR

Constructed variable: NHOSP = AP5103
3.11) **Degree of satisfaction with the current job:**

**Table AP**

Variable \( AP0304 = \text{SATISFACTION WITH THE CURRENT JOB} \)

-2 = MISSING: NOT APPLICABLE
-1 = MISSING: NOT AVAILABLE
0 = TOTAL DISSATISFACTION
1
2
3
4
5
6
7
8
9
10 = TOTAL SATISFACTION

Constructed variable: \( \text{SATIS} = 0,1,2,3,4,5,6,7,8,9,10 \)

3.12) **Firm size:**

**Table AP**

Variable \( AP27 = \text{NUMBER OF EMPLOYEES OF THE WHOLE FIRM OF EMPLOYMENT} \)

-2 = MISSING: NOT APPLICABLE
-1 = MISSING: NOT AVAILABLE
1 = FEWER THAN 20 EMPLOYEES
2 = 20-200 EMPLOYEES
3 = 200-2000 EMPLOYEES
4 = 2000 OR MORE EMPLOYEES
5 = NOT APPLICABLE, SELF-EMPLOYED WITH NO OTHER EMPLOYEES

Constructed dummies:

DSIZE1: \( AP27 = 1 \) (base group)
DSIZE2: \( AP27 = 2 \)
DSIZE3: \( AP27 = 3 \)
DSIZE4: \( AP27 = 4 \)
4) Construction of industry dummies

Table AP

<table>
<thead>
<tr>
<th>Variable</th>
<th>ABRANCHE = INDUSTRY (3-digit classification)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AGRICULTURE AND FORESTRY</td>
</tr>
<tr>
<td>2</td>
<td>FISHING INDUSTRY</td>
</tr>
<tr>
<td>3</td>
<td>ENERGY AND WATER</td>
</tr>
<tr>
<td>4</td>
<td>MINING</td>
</tr>
<tr>
<td>5</td>
<td>CHEMICAL INDUSTRY</td>
</tr>
<tr>
<td>6</td>
<td>SYNTHETIC FIBER INDUSTRY</td>
</tr>
<tr>
<td>7</td>
<td>CLAY, STONE, EARTH</td>
</tr>
<tr>
<td>8</td>
<td>IRON AND STEEL INDUSTRY</td>
</tr>
<tr>
<td>9</td>
<td>MECHANICAL ENGINEERING</td>
</tr>
<tr>
<td>10</td>
<td>ELECTRICAL AND PRECISION ENGINEERING</td>
</tr>
<tr>
<td>11</td>
<td>WOOD, PAPER, AND PRINT</td>
</tr>
<tr>
<td>12</td>
<td>CLOTHING TRADE</td>
</tr>
<tr>
<td>13</td>
<td>FOOD INDUSTRY</td>
</tr>
<tr>
<td>14</td>
<td>CONSTRUCTION</td>
</tr>
<tr>
<td>15</td>
<td>CONSTRUCTION RELATED</td>
</tr>
<tr>
<td>16</td>
<td>WHOLESALE</td>
</tr>
<tr>
<td>17</td>
<td>TRADING AGENTS</td>
</tr>
<tr>
<td>18</td>
<td>RETAIL</td>
</tr>
<tr>
<td>19</td>
<td>FEDERAL TRAIN SYSTEM</td>
</tr>
<tr>
<td>20</td>
<td>FEDERAL POSTAL SYSTEM</td>
</tr>
<tr>
<td>21</td>
<td>OTHER TRAFFIC SYSTEM</td>
</tr>
<tr>
<td>22</td>
<td>BANKS, SAVINGS INSTITUTIONS</td>
</tr>
<tr>
<td>23</td>
<td>INSURANCE COMPANIES</td>
</tr>
<tr>
<td>24</td>
<td>RESTAURANTS</td>
</tr>
<tr>
<td>25</td>
<td>SERVICE INDUSTRY</td>
</tr>
<tr>
<td>26</td>
<td>JANITORS, WASTE REMOVERS</td>
</tr>
<tr>
<td>27</td>
<td>EDUCATION, SPORT</td>
</tr>
<tr>
<td>28</td>
<td>HEALTH SERVICES</td>
</tr>
<tr>
<td>29</td>
<td>LEGAL SERVICES</td>
</tr>
<tr>
<td>30</td>
<td>OTHER SERVICES</td>
</tr>
<tr>
<td>31</td>
<td>CHURCHES, ASSOCIATIONS</td>
</tr>
<tr>
<td>32</td>
<td>PRIVATE HOUSEHOLDS</td>
</tr>
<tr>
<td>33</td>
<td>REGIONAL AUTHORITY</td>
</tr>
<tr>
<td>34</td>
<td>SOCIAL SECURITY</td>
</tr>
<tr>
<td>35</td>
<td>OTHER INDUSTRY</td>
</tr>
<tr>
<td>36</td>
<td>INCORRECT ANSWER TO INDUSTRY</td>
</tr>
<tr>
<td>37</td>
<td>NO ANSWER TO INDUSTRY</td>
</tr>
</tbody>
</table>
Constructed dummies:

DIND1: ABRANCHE = 1.2 (base group)
DIND2: ABRANCHE = 3.4
DIND3: ABRANCHE = 5
DIND4: ABRANCHE = 6
DIND5: ABRANCHE = 7
DIND6: ABRANCHE = 8
DIND7: ABRANCHE = 9
DIND8: ABRANCHE = 10
DIND9: ABRANCHE = 11
DIND10: ABRANCHE = 12
DIND11: ABRANCHE = 13
DIND12: ABRANCHE = 14, 15
DIND13: ABRANCHE = 16
DIND14: ABRANCHE = 17, 18
DIND15: ABRANCHE = 19
DIND16: ABRANCHE = 20
DIND17: ABRANCHE = 21
DIND18: ABRANCHE = 22
DIND19: ABRANCHE = 23
DIND20: ABRANCHE = 24, 25, 26
DIND21: ABRANCHE = 27
DIND22: ABRANCHE = 28
DIND23: ABRANCHE = 29
DIND24: ABRANCHE = 31, 32
DIND25: ABRANCHE = 33
DIND26: ABRANCHE = 34
DINDMIS: ABRANCHE = 30, 35, 36, 37
Appendix 4.B: Estimated Wage Equations in the Sample Selection Model

In this Appendix I report the results for the estimated wage equations which have been used to derive the industry wage differentials presented in Section 4.3.

Table 4.B1 gives the estimates of the probit overtime work equation (4.2') used in my sample selection model. The probability that employees work overtime hours is estimated with the ML method as a function of a number of variables which are supposed to affect individuals' propensity to overtime work. For the construction of the explanatory variables, I defined several sets of dummies. Since the overtime work equation includes a constant, I omitted a dummy variable from each set and treated it as having a zero additional effect - with respect to the mean effect represented by the constant term - on the probability of working overtime. The reference groups for each set of dummy variables are the following: unskilled blue-collar workers for the skill variables (292 cases); German nationality employees for the nationality variables (1,789 cases); employees in firms with fewer than 20 employees for the firm size variables (480 cases); employees working in the agriculture, forestry and fishery sector for the industry variables (35 cases).

As far as the significance of each coefficient for the variables in the model is concerned, we note that a relevant role is played by the number of children in the household, some of the nationalities of the workers (Turkish or Italian nationality and the group of all the other unspecified nationalities), the highest skill level (white-collar workers with extensive leadership responsibilities), and a size of the firm of employment between 20 and 200 employees. The coefficients of the age variables have the expected signs, but are not significantly different from zero. The results for the skill variables are mixed. Among blue-collar workers, a higher skill level seems to increase the probability of doing overtime work, but the effect of skill differences is not statistically significant. Among white-collar workers we generally observe the opposite phenomenon, but only at the highest level of professional qualification the influence of skill on the probability of overtime work is significantly different from zero. Nationalities different from the German one imply a lower probability of working overtime and this effect is statistically significant in three of the five cases delineated by the nationality dummy variables. The number of children in the household, the ownership of a second house or apartment, and the existence of a mortgage on the house/apartment which is the main residence of the household are all expected to

186
### TABLE 4.B1
Estimated PROBIT overtime work equation in a sample selection model with controls for human capital and working conditions. 1984 (standard errors in parentheses)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.154</td>
<td>(0.390)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age/10</td>
<td>-0.099</td>
<td>(0.174)</td>
<td>3.963</td>
<td>2,944</td>
</tr>
<tr>
<td>Age²/100</td>
<td>0.003</td>
<td>(0.022)</td>
<td>16.947</td>
<td>2,944</td>
</tr>
</tbody>
</table>

**Skill variables:**
- Unskilled worker with on-the-job training: 0.008 (0.095) 0.290 855
- Trained worker: 0.068 (0.100) 0.274 807
- Foreman: 0.195 (0.148) 0.042 124
- Master: 0.224 (0.203) 0.018 54
- White-collar industrial worker: -0.014 (0.226) 0.014 42
- White-collar worker in basic positions: -0.278 (0.184) 0.029 84
- White-collar worker with advanced qualifications: -0.084 (0.119) 0.139 408
- Highly trained white-collar worker: 0.030 (0.130) 0.084 248
- White-collar worker with extensive leadership responsibilities: -1.000** (0.343) 0.010 30

**Nationality variables:**
- Turkey: -0.469** (0.098) 0.116 342
- Yugoslavia: -0.076 (0.103) 0.072 213
- Greece: -0.189 (0.123) 0.052 154
- Italy: -0.357** (0.103) 0.082 240
- Other nationality: -0.472** (0.112) 0.068 199
- Dummy for missing nationality: -0.796 (0.600) 0.002 7
- Number of children under 16: 0.077** (0.026) 1.004 2,944
- Dummy for second house: -0.010 (0.162) 0.025 73
- Dummy for mortgage: -0.072 (0.066) 0.195 573
- Number of nights in hospital: -0.00002 (0.003) 1.711 2,944
- Degree of satisfaction with the current job [0-10]: 0.0009 (0.011) 7.533 2,930

**Firm size variables:**
- 20-200 employees: 0.210** (0.079) 0.295 869
- 200-2,000 employees: 0.136 (0.085) 0.253 745
- 2,000 or more employees: 0.167 (0.086) 0.289 850

**Industry variables:**
- Energy, water and mining: -0.225 (0.275) 0.026 77
- Chemical: -0.352 (0.257) 0.047 137
- Rubber: -0.105 (0.288) 0.019 56
- Stone, clay and glass: -0.083 (0.281) 0.021 63
- Iron and steel: -0.142 (0.236) 0.133 393
- Machinery, excl. elec.: -0.167 (0.237) 0.123 362

(continued)
<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electrical machinery</td>
<td>-0.274</td>
<td>(0.251)</td>
<td>0.054</td>
<td>159</td>
</tr>
<tr>
<td>Lumber, wood, paper and printing</td>
<td>0.151</td>
<td>(0.252)</td>
<td>0.043</td>
<td>126</td>
</tr>
<tr>
<td>Textile and apparel</td>
<td>-0.162</td>
<td>(0.269)</td>
<td>0.029</td>
<td>85</td>
</tr>
<tr>
<td>Food, beverages and tobacco</td>
<td>-0.059</td>
<td>(0.264)</td>
<td>0.031</td>
<td>90</td>
</tr>
<tr>
<td>Construction</td>
<td>-0.236</td>
<td>(0.234)</td>
<td>0.135</td>
<td>398</td>
</tr>
<tr>
<td>Wholesale trade</td>
<td>0.422</td>
<td>(0.288)</td>
<td>0.017</td>
<td>51</td>
</tr>
<tr>
<td>Retail trade</td>
<td>-0.350</td>
<td>(0.270)</td>
<td>0.031</td>
<td>91</td>
</tr>
<tr>
<td>Railroads</td>
<td>-0.765</td>
<td>(0.409)</td>
<td>0.007</td>
<td>22</td>
</tr>
<tr>
<td>Mail service</td>
<td>-0.341</td>
<td>(0.397)</td>
<td>0.007</td>
<td>20</td>
</tr>
<tr>
<td>Other transport and communications</td>
<td>0.053</td>
<td>(0.262)</td>
<td>0.032</td>
<td>94</td>
</tr>
<tr>
<td>Banking</td>
<td>0.182</td>
<td>(0.299)</td>
<td>0.016</td>
<td>47</td>
</tr>
<tr>
<td>Insurance</td>
<td>-0.245</td>
<td>(0.385)</td>
<td>0.007</td>
<td>20</td>
</tr>
<tr>
<td>Personal services</td>
<td>0.136</td>
<td>(0.299)</td>
<td>0.015</td>
<td>44</td>
</tr>
<tr>
<td>Entertainment</td>
<td>-0.019</td>
<td>(0.290)</td>
<td>0.019</td>
<td>56</td>
</tr>
<tr>
<td>Health services</td>
<td>0.095</td>
<td>(0.297)</td>
<td>0.017</td>
<td>49</td>
</tr>
<tr>
<td>Legal and business services</td>
<td>-0.168</td>
<td>(0.360)</td>
<td>0.008</td>
<td>23</td>
</tr>
<tr>
<td>Non-profit organizations and private households</td>
<td>-0.283</td>
<td>(0.323)</td>
<td>0.013</td>
<td>37</td>
</tr>
<tr>
<td>Local collective organizations</td>
<td>-0.170</td>
<td>(0.258)</td>
<td>0.042</td>
<td>123</td>
</tr>
<tr>
<td>Social security</td>
<td>-0.247</td>
<td>(0.419)</td>
<td>0.005</td>
<td>15</td>
</tr>
<tr>
<td>Dummy for missing industry</td>
<td>-0.140</td>
<td>(0.239)</td>
<td>0.092</td>
<td>271</td>
</tr>
</tbody>
</table>

Log-likelihood                     -1727.3
Restricted (slopes=0) log-likelihood -1788.8
$\chi^2$ (51)                        122.95
Significance level                  0.0000000009
Sample size                         2.944

* Statistically different from 0 at the 5% significance level.
** Statistically different from 0 at the 1% significance level.
increase the probability of doing overtime work, but of these three variables only the first one presents a statistically significant coefficient. The number of nights spent in a hospital in the previous year and the degree of satisfaction with the current job in a scale from 0 to 10 are supposed to provide some indication about working conditions. The coefficients of these two variables have the expected signs, in the sense that less dangerous or more pleasant working conditions tend to be associated with a higher probability of overtime work. However, neither coefficient is significantly different from zero. A relatively larger size of the firm of current employment is also affecting positively the probability of working overtime, but the effect of firm size is statistically significant only in the case of medium-sized firms (between 20 and 200 employees). Finally, none of the coefficients of the industry dummy variables included in the model is significantly different from zero. This outcome seems to confirm the result obtained from the chi-square test illustrated in Section 4.2, since the propensity to do overtime work does not seem to be influenced by the affiliation to any particular industry.

Table 4.B2 gives the estimates of two-digit industry wage differences from the regression of log hourly earnings on industry dummy variables only, in a sample selection approach. This represents the restricted specification of the model expressed by equations (4.1') and (4.2'), as illustrated in Section 4.2. The estimated coefficients are used to calculate the normalized industry differentials in deviation form - as deviations from the employment-weighted mean differential - reported in the first column of Table 4.1.

All the industry dummies coefficients except one (that for retail trade) are statistically significant individually at the 5% level and 21 of the 26 coefficients are also significant at the 1% level. The F statistic shows that they are also jointly statistically significant at the 1% level. We note that here the coefficient for the Heckman's λ is significantly different from zero at the 1% level, revealing a sample selection bias problem in this specification of the model. As already stressed, however, our estimates of the regression coefficients obtained with the Heckman's method are still consistent.

In Table 4.B3 I present the results for the regression of log hourly earnings on both industry dummy variables and a set of controls for labour quality, demographic and working conditions, in a sample selection model. It therefore represents the general specification of equation (4.1'). The estimated industry wage coefficients reported in this Table are used to calculate the normalized industry differentials in deviation form appearing in the third column of Table 4.1. For the definition of control variables, I constructed here, as well, various sets
<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.481&quot;</td>
<td>(0.077)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy, water and mining</td>
<td>0.436&quot;</td>
<td>(0.082)</td>
<td>0.027</td>
<td>55</td>
</tr>
<tr>
<td>Chemical</td>
<td>0.442&quot;</td>
<td>(0.076)</td>
<td>0.051</td>
<td>105</td>
</tr>
<tr>
<td>Rubber</td>
<td>0.210&quot;</td>
<td>(0.087)</td>
<td>0.019</td>
<td>39</td>
</tr>
<tr>
<td>Stone, clay and glass</td>
<td>0.296&quot;</td>
<td>(0.085)</td>
<td>0.021</td>
<td>44</td>
</tr>
<tr>
<td>Iron and steel</td>
<td>0.252&quot;</td>
<td>(0.072)</td>
<td>0.135</td>
<td>280</td>
</tr>
<tr>
<td>Machinery, excl. elec.</td>
<td>0.354&quot;</td>
<td>(0.072)</td>
<td>0.124</td>
<td>257</td>
</tr>
<tr>
<td>Electrical machinery</td>
<td>0.367&quot;</td>
<td>(0.076)</td>
<td>0.056</td>
<td>117</td>
</tr>
<tr>
<td>Lumber, wood, paper and printing</td>
<td>0.213&quot;</td>
<td>(0.079)</td>
<td>0.037</td>
<td>76</td>
</tr>
<tr>
<td>Textile and apparel</td>
<td>0.259&quot;</td>
<td>(0.081)</td>
<td>0.030</td>
<td>62</td>
</tr>
<tr>
<td>Food, beverages and tobacco</td>
<td>0.173&quot;</td>
<td>(0.081)</td>
<td>0.029</td>
<td>60</td>
</tr>
<tr>
<td>Construction</td>
<td>0.270&quot;</td>
<td>(0.072)</td>
<td>0.139</td>
<td>289</td>
</tr>
<tr>
<td>Wholesale trade</td>
<td>0.326&quot;</td>
<td>(0.095)</td>
<td>0.013</td>
<td>26</td>
</tr>
<tr>
<td>Retail trade</td>
<td>0.119</td>
<td>(0.080)</td>
<td>0.034</td>
<td>71</td>
</tr>
<tr>
<td>Railroads</td>
<td>0.233&quot;</td>
<td>(0.105)</td>
<td>0.009</td>
<td>19</td>
</tr>
<tr>
<td>Mail service</td>
<td>0.291&quot;</td>
<td>(0.109)</td>
<td>0.008</td>
<td>16</td>
</tr>
<tr>
<td>Other transport and communications</td>
<td>0.307&quot;</td>
<td>(0.081)</td>
<td>0.028</td>
<td>59</td>
</tr>
<tr>
<td>Banking</td>
<td>0.383&quot;</td>
<td>(0.093)</td>
<td>0.014</td>
<td>28</td>
</tr>
<tr>
<td>Insurance</td>
<td>0.691&quot;</td>
<td>(0.110)</td>
<td>0.007</td>
<td>15</td>
</tr>
<tr>
<td>Personal services</td>
<td>-0.219&quot;</td>
<td>(0.093)</td>
<td>0.014</td>
<td>28</td>
</tr>
<tr>
<td>Entertainment</td>
<td>0.542&quot;</td>
<td>(0.087)</td>
<td>0.018</td>
<td>38</td>
</tr>
<tr>
<td>Health services</td>
<td>0.342&quot;</td>
<td>(0.091)</td>
<td>0.015</td>
<td>31</td>
</tr>
<tr>
<td>Legal and business services</td>
<td>0.582&quot;</td>
<td>(0.108)</td>
<td>0.008</td>
<td>16</td>
</tr>
<tr>
<td>Non-profit organizations and private households</td>
<td>0.397&quot;</td>
<td>(0.093)</td>
<td>0.014</td>
<td>28</td>
</tr>
<tr>
<td>Local collective organizations</td>
<td>0.328&quot;</td>
<td>(0.077)</td>
<td>0.042</td>
<td>88</td>
</tr>
<tr>
<td>Social security</td>
<td>0.400&quot;</td>
<td>(0.121)</td>
<td>0.005</td>
<td>11</td>
</tr>
<tr>
<td>Dummy for missing industry</td>
<td>0.248&quot;</td>
<td>(0.073)</td>
<td>0.092</td>
<td>191</td>
</tr>
<tr>
<td>HECKMAN'S $\lambda$</td>
<td>-0.164&quot;</td>
<td>(0.064)</td>
<td>-0.473</td>
<td>2,072</td>
</tr>
</tbody>
</table>

Correlation between regression and selection equation disturbances ($p_{e_1,e_2}$) 0.486

Standard error of the regression 0.338*

$F$-statistic (27, 2044) 9.547**

$R^2$ 0.100

Sample size 2,072

* Selectivity corrected estimate of the standard error of the regression.

" Statistically different from 0 at the 5% significance level.

** Statistically different from 0 at the 1% significance level. The $F$ test that all the estimated slope coefficients jointly equal 0 rejects at the 1% level. The 1% critical point is $F_{27, 2044} = 1.739$. 

190
TABLE 4.B3
Estimated wage equation in a sample selection model with controls for human capital and working conditions. 1984 (standard errors in parentheses)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.569** (0.100)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age/10</td>
<td>0.380** (0.038)</td>
<td>4.012</td>
<td>2.072</td>
<td></td>
</tr>
<tr>
<td>Age²/100</td>
<td>-0.043** (0.005)</td>
<td>17.356</td>
<td>2.072</td>
<td></td>
</tr>
<tr>
<td>Tenure/10</td>
<td>0.064** (0.019)</td>
<td>1.159</td>
<td>1.971</td>
<td></td>
</tr>
<tr>
<td>Tenure²/100</td>
<td>-0.014** (0.005)</td>
<td>2.108</td>
<td>1.971</td>
<td></td>
</tr>
</tbody>
</table>

German education variables:
- Short-course secondary school: 0.016 (0.025) 0.476 986
- Intermediate type of secondary school: 0.071* (0.032) 0.093 193
- Technical high school, academically-oriented secondary school: 0.076 (0.041) 0.027 56
- Technical college, engineering school: 0.147** (0.042) 0.029 60
- College, university: 0.264** (0.044) 0.031 64

Foreign education variables:
- Compulsory school without final examination: 0.071** (0.025) 0.120 249
- Compulsory school with final examination: 0.046 (0.025) 0.167 346
- Further schooling: 0.062 (0.038) 0.026 53
- Specialized professional school: 0.102** (0.033) 0.044 92
- College, university: -0.159 (0.082) 0.004 9

Skill variables:
- Unskilled worker with on-the-job training: 0.017 (0.019) 0.298 618
- Trained worker: 0.086** (0.021) 0.266 552
- Foreman: 0.141** (0.034) 0.038 79
- Master: 0.328** (0.047) 0.016 34
- White-collar industrial worker: 0.247** (0.049) 0.014 29
- White-collar worker in basic positions: 0.005 (0.037) 0.032 66
- White-collar worker with advanced qualifications: 0.219** (0.026) 0.138 286
- Highly trained white-collar worker: 0.448** (0.033) 0.080 165
- White-collar worker with extensive leadership responsibilities: 0.735** (0.061) 0.013 27

Marital status variables:
- Married, living with spouse: 0.100** (0.019) 0.448 928
- Married, permanently separated: 0.450** (0.080) 0.004 9
- Divorced: 0.060 (0.043) 0.017 35
- Widowed: 0.133* (0.060) 0.008 17

Number of nights in hospital: -0.001* (0.006) 1.751 2.072

Degree of satisfaction with the current job [0-10]: 0.005* (0.002) 7.528 2.060

Firm size variables:
- 20-200 employees: 0.040* (0.018) 0.282 585

(continued)
<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>200-2,000 employees</td>
<td>0.070**</td>
<td>(0.018)</td>
<td>0.254</td>
<td>527</td>
</tr>
<tr>
<td>2,000 or more employees</td>
<td>0.122**</td>
<td>(0.019)</td>
<td>0.292</td>
<td>606</td>
</tr>
<tr>
<td>Industry variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy, water and mining</td>
<td>0.221**</td>
<td>(0.060)</td>
<td>0.027</td>
<td>55</td>
</tr>
<tr>
<td>Chemical</td>
<td>0.194**</td>
<td>(0.057)</td>
<td>0.051</td>
<td>105</td>
</tr>
<tr>
<td>Rubber</td>
<td>0.104</td>
<td>(0.063)</td>
<td>0.019</td>
<td>39</td>
</tr>
<tr>
<td>Stone, clay and glass</td>
<td>0.146*</td>
<td>(0.062)</td>
<td>0.021</td>
<td>44</td>
</tr>
<tr>
<td>Iron and steel</td>
<td>0.130*</td>
<td>(0.052)</td>
<td>0.135</td>
<td>280</td>
</tr>
<tr>
<td>Machinery, excl. elec.</td>
<td>0.170**</td>
<td>(0.053)</td>
<td>0.124</td>
<td>257</td>
</tr>
<tr>
<td>Electrical machinery</td>
<td>0.139*</td>
<td>(0.056)</td>
<td>0.056</td>
<td>117</td>
</tr>
<tr>
<td>Lumber, wood, paper and printing</td>
<td>0.147**</td>
<td>(0.057)</td>
<td>0.037</td>
<td>76</td>
</tr>
<tr>
<td>Textile and apparel</td>
<td>0.123*</td>
<td>(0.059)</td>
<td>0.030</td>
<td>62</td>
</tr>
<tr>
<td>Food, beverages and tobacco</td>
<td>0.008</td>
<td>(0.059)</td>
<td>0.029</td>
<td>60</td>
</tr>
<tr>
<td>Construction</td>
<td>0.153**</td>
<td>(0.053)</td>
<td>0.139</td>
<td>289</td>
</tr>
<tr>
<td>Wholesale trade</td>
<td>0.031</td>
<td>(0.071)</td>
<td>0.013</td>
<td>26</td>
</tr>
<tr>
<td>Retail trade</td>
<td>0.005</td>
<td>(0.059)</td>
<td>0.034</td>
<td>71</td>
</tr>
<tr>
<td>Railroads</td>
<td>0.039</td>
<td>(0.079)</td>
<td>0.009</td>
<td>19</td>
</tr>
<tr>
<td>Mail service</td>
<td>0.120</td>
<td>(0.080)</td>
<td>0.008</td>
<td>16</td>
</tr>
<tr>
<td>Other transport and communications</td>
<td>0.098</td>
<td>(0.059)</td>
<td>0.028</td>
<td>59</td>
</tr>
<tr>
<td>Banking</td>
<td>0.015</td>
<td>(0.069)</td>
<td>0.014</td>
<td>28</td>
</tr>
<tr>
<td>Insurance</td>
<td>0.272**</td>
<td>(0.081)</td>
<td>0.007</td>
<td>15</td>
</tr>
<tr>
<td>Personal services</td>
<td>-0.214**</td>
<td>(0.067)</td>
<td>0.014</td>
<td>28</td>
</tr>
<tr>
<td>Entertainment</td>
<td>0.093</td>
<td>(0.064)</td>
<td>0.018</td>
<td>38</td>
</tr>
<tr>
<td>Health services</td>
<td>-0.003</td>
<td>(0.066)</td>
<td>0.015</td>
<td>31</td>
</tr>
<tr>
<td>Legal and business services</td>
<td>0.173*</td>
<td>(0.079)</td>
<td>0.008</td>
<td>16</td>
</tr>
<tr>
<td>Non-profit organizations and private households</td>
<td>0.048</td>
<td>(0.068)</td>
<td>0.014</td>
<td>28</td>
</tr>
<tr>
<td>Local collective organizations</td>
<td>0.062</td>
<td>(0.057)</td>
<td>0.042</td>
<td>88</td>
</tr>
<tr>
<td>Social security</td>
<td>0.050</td>
<td>(0.089)</td>
<td>0.005</td>
<td>11</td>
</tr>
<tr>
<td>Dummy for missing industry</td>
<td>0.091</td>
<td>(0.053)</td>
<td>0.092</td>
<td>191</td>
</tr>
<tr>
<td><strong>HECKMAN'S λ</strong></td>
<td>-0.070</td>
<td>(0.078)</td>
<td>-0.473</td>
<td>2.072</td>
</tr>
</tbody>
</table>

Correlation between regression and selection equation disturbances ($p_{e_1e_2}$) 0.297
Standard error of the regression 0.237*
F-statistic (59, 2012) 38.310**
$R^2$ 0.515
Sample size 2.072

* Selectivity corrected estimate of the standard error of the regression.
* Statistically different from 0 at the 5% significance level.
** Statistically different from 0 at the 1% significance level. The F test that all the estimated slope coefficients jointly equal 0 rejects at the 1% level. The 1% critical point is $F_{m}(59, 2012) = 1.477$. 

192
of dummy variables. Given that the wage regression also includes a constant, I omitted a dummy variable from each set and treated it as having a zero additional effect on wages. The base groups for each set of dummies in this equation are: employees who did not receive any education in Germany for the German education variables (713 cases); employees who did not receive any education outside Germany for the foreign education variables (1,323 cases); unskilled blue-collar workers for the skill variables (216 cases); single employees for the marital status variables (1,083 cases); employees in firms with fewer than 20 employees for the firm size variables (354 cases); employees working in the agriculture, forestry and fishery sector for industry variables (23 cases).

The choice of the reference groups - the omitted dummy variables - is completely arbitrary and does not affect the statistical properties of the model as a whole. However, if we do not take this arbitrariness into account, the interpretation of the estimated coefficients and of their standard errors may be very misleading. The coefficients for the dummy variables included in the regression, in fact, must be interpreted as the relative wage differences with respect to an individual characterized by the combination of all the aspects associated with each of the base groups. For this reason in the main text I present a normalized measure of industry differentials, which are the variables of my major concern in this study.

With reference to the statistical significance of the coefficients of the single control variables, we notice that in the wage equation a relevant role is played by almost all controls. Age, tenure in the current job, half of the education variables, 7 of the 9 skill level dummies, 3 of the 4 marital status variables, health conditions measured through the number of nights spent in a hospital, the degree of satisfaction with the current job, and all firm size dummies exhibit coefficients which are significantly different from zero either at the 1% or at the 5% significance level. It is worth noting that in earlier specifications of the econometric model (not presented here), the set of dummy variables for foreign nationalities was also included among the explanatory variables of the wage equation (4.1') with controls, as well as in the probit overtime work equation (4.2'). After the introduction of variables for foreign education and the Heckman's correction for sample selection bias, all the coefficients of the nationality variables were insignificantly different from zero both at the 1% and 5% level. Even in a

41 The sum of the numbers of cases for all the German education variables and the foreign education variables exceeds the total number of observations in the sample because a certain amount of employees (36 cases) received some education both inside and outside Germany.
simple OLS estimate of the wage equation, without taking sample selection into account, only one of the five coefficients of the foreign nationality dummies (Yugoslavia) was significantly different from zero and only at the 5% significance level. Moreover, the nationality variables had a rather ambiguous effect on wages. Three of them (Yugoslavia, Greece and Italy) presented a positive coefficient (although two of these not significantly different from zero) and the other two (Turkey and other nationality) a negative coefficient (both statistically insignificant). It seems therefore that the expected negative impact of a foreign nationality on average wages operates by decreasing the probability of undertaking more highly paid overtime work, rather than by directly reducing straight-time earnings.

Human capital and working conditions as a whole are very important in explaining variations in individual wages. When these controls are introduced in the wage regression, the standard error of the regression is reduced by 30 percentage points and the adjusted $R^2$ increases from 10 to 52 percent. With respect to the raw estimates of Table 4.B2, we observe that the industry affiliation effect tends to decrease after controlling for human capital and working conditions. In this general specification of the wage model, only 12 of the 26 industry dummies coefficients remain statistically significant at the 5% level and 7 of them also at the 1% level. However, estimated industry wage differences continue to be jointly statistically significant at the 1% level. We can also note that the coefficient for the Heckman’s $\lambda$ in our sample selection model is not significantly different from zero, indicating that we fail to reject the null hypothesis of no sample selection bias introduced with the elimination of employees doing overtime work.
**Appendix 4.C: Estimated Wage Differentials for Inter-Country Comparisons**

**TABLE 4.C1**

Wage differentials for the **UNITED STATES** and **AUSTRALIA**: deviations from the employment-weighted mean differential

Aggregation of the original differentials into a common classification of industry sectors by employment-weighted averages

<table>
<thead>
<tr>
<th>Industry</th>
<th>With controls</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>United States</td>
</tr>
<tr>
<td>1. Mining</td>
<td>0.241</td>
</tr>
<tr>
<td>2. Manufacturing</td>
<td>0.105</td>
</tr>
<tr>
<td>3. Public utilities</td>
<td>0.259</td>
</tr>
<tr>
<td>4. Construction</td>
<td>0.126</td>
</tr>
<tr>
<td>5. Trade</td>
<td>-0.124</td>
</tr>
<tr>
<td>6. Transport</td>
<td>0.132</td>
</tr>
<tr>
<td>7. Communication</td>
<td>0.171</td>
</tr>
<tr>
<td>8. Finance, real estate, business services</td>
<td>0.030</td>
</tr>
<tr>
<td>9. Social, community services</td>
<td>-0.083</td>
</tr>
<tr>
<td>10. Recreation, personal services</td>
<td>-0.199</td>
</tr>
</tbody>
</table>

Mean of differentials
Mean of differentials in absolute value
SD of differentials
Sample size

---


*For the United States, the sample considered includes male and female workers; for Australia, the sample consists only of male workers.*
TABLE 4.C2
Wage differentials for the United States and Germany
deviations from the employment-weighted mean differential
Aggregation of the original differentials into a common classification
of industry sectors by employment-weighted averages

<table>
<thead>
<tr>
<th>Industry</th>
<th>Without controls</th>
<th>With controls</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Mining, public utilities</td>
<td>0.479</td>
<td>0.209</td>
</tr>
<tr>
<td>2. Chemical</td>
<td>0.397</td>
<td>0.200</td>
</tr>
<tr>
<td>3. Rubber</td>
<td>0.038</td>
<td>-0.020</td>
</tr>
<tr>
<td>4. Stone, clay, glass</td>
<td>0.357</td>
<td>0.026</td>
</tr>
<tr>
<td>5. Basic metals</td>
<td>0.357</td>
<td>0.030</td>
</tr>
<tr>
<td>6. Machinery excl. elec.</td>
<td>0.309</td>
<td>0.150</td>
</tr>
<tr>
<td>7. Electrical machinery, equipment</td>
<td>0.195</td>
<td>0.021</td>
</tr>
<tr>
<td>8. Wood, paper, printing</td>
<td>0.079</td>
<td>0.035</td>
</tr>
<tr>
<td>9. Textile, apparel</td>
<td>-0.245</td>
<td>-0.216</td>
</tr>
<tr>
<td>10. Food, beverages, tobacco</td>
<td>0.094</td>
<td>-0.172</td>
</tr>
<tr>
<td>11. Construction</td>
<td>0.216</td>
<td>0.086</td>
</tr>
<tr>
<td>12. Wholesale trade</td>
<td>0.171</td>
<td>-0.008</td>
</tr>
<tr>
<td>13. Retail trade</td>
<td>-0.316</td>
<td>-0.247</td>
</tr>
<tr>
<td>14. Transport, communication</td>
<td>0.294</td>
<td>0.061</td>
</tr>
<tr>
<td>15. Banking</td>
<td>0.084</td>
<td>0.128</td>
</tr>
<tr>
<td>16. Insurance</td>
<td>0.105</td>
<td>0.185</td>
</tr>
<tr>
<td>17. Personal services</td>
<td>-0.329</td>
<td>-0.381</td>
</tr>
<tr>
<td>18. Recreation, cultural services</td>
<td>-0.070</td>
<td>0.167</td>
</tr>
<tr>
<td>19. Health services</td>
<td>-0.007</td>
<td>-0.047</td>
</tr>
<tr>
<td>20. Business services</td>
<td>0.103</td>
<td>0.074</td>
</tr>
<tr>
<td>21. Household services</td>
<td>-0.776</td>
<td>-0.033</td>
</tr>
<tr>
<td>22. Social services</td>
<td>-0.194</td>
<td>0.114</td>
</tr>
</tbody>
</table>

Mean of differentials                    0.061            | 0.017         | 0.022            | 0.006
Mean of differentials in absolute value | 0.237            | 0.119         | 0.131            | 0.057
SD of differentials                     0.294            | 0.154         | 0.159            | 0.069
Sample sized                            10.28           | 4.389         | 11.512           | 4.389

b Source: my results from the SOEP. Estimation method: OLS. No aggregation.
d For both the United States and Germany, the samples considered include male and female workers.
* Statistically significant at the 5% level.
** Statistically significant at the 1% level.
TABLE 4.C3
Wage differentials for the UNITED STATES and AUSTRIA:
deviations from the employment-weighted mean differential
Aggregation of the original differentials into a common classification
of industry sectors by employment-weighted averages

<table>
<thead>
<tr>
<th>Industry</th>
<th>United States</th>
<th>Austria</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1984</td>
<td>1983</td>
</tr>
<tr>
<td>1. Public utilities</td>
<td>0.259</td>
<td>-0.004</td>
</tr>
<tr>
<td>2. Mining</td>
<td>0.241</td>
<td>0.067</td>
</tr>
<tr>
<td>3. Food, beverages, tobacco</td>
<td>0.067</td>
<td>-0.033</td>
</tr>
<tr>
<td>4. Textile</td>
<td>0.011</td>
<td>-0.086</td>
</tr>
<tr>
<td>5. Apparel</td>
<td>-0.127</td>
<td>-0.115</td>
</tr>
<tr>
<td>6. Leather</td>
<td>-0.082</td>
<td>-0.066</td>
</tr>
<tr>
<td>7. Wood</td>
<td>-0.002</td>
<td>-0.067</td>
</tr>
<tr>
<td>8. Paper</td>
<td>0.141</td>
<td>0.050</td>
</tr>
<tr>
<td>9. Printing</td>
<td>0.092</td>
<td>0.085</td>
</tr>
<tr>
<td>10. Chemical</td>
<td>0.177</td>
<td>0.085</td>
</tr>
<tr>
<td>11. Stone, clay, glass</td>
<td>0.085</td>
<td>0.015</td>
</tr>
<tr>
<td>12. Metals, machinery</td>
<td>0.150</td>
<td>0.024</td>
</tr>
<tr>
<td>13. Construction</td>
<td>0.126</td>
<td>0.043</td>
</tr>
<tr>
<td>14. Trade</td>
<td>-0.105</td>
<td>-0.030</td>
</tr>
<tr>
<td>15. Restaurants, hotels</td>
<td>-0.189</td>
<td>0.018</td>
</tr>
<tr>
<td>16. Transport, communication</td>
<td>0.145</td>
<td>-0.032</td>
</tr>
<tr>
<td>17. Banking</td>
<td>0.068</td>
<td>0.024</td>
</tr>
<tr>
<td>18. Business services</td>
<td>0.016</td>
<td>0.016</td>
</tr>
<tr>
<td>19. Recreation, cultural services</td>
<td>-0.141</td>
<td>0.050</td>
</tr>
<tr>
<td>20. Medical, health, social services</td>
<td>-0.046</td>
<td>0.023</td>
</tr>
<tr>
<td>21. Education</td>
<td>-0.194</td>
<td>0.059</td>
</tr>
<tr>
<td>22. Personal, household services</td>
<td>-0.217</td>
<td>-0.001</td>
</tr>
</tbody>
</table>

Mean of differentials 0.022 0.006
Mean of differentials in absolute value 0.122 0.045
SD of differentials 0.143 0.055
Sample size\(^c\) 11.512 11.829


\(^c\) For both the United States and Austria, the samples considered include male and female workers.
TABLE 4.C4
Wage differentials for the UNITED STATES and SWEDEN:
deviations from the employment-weighted mean differential
Aggregation of the original differentials into a common classification
of industry sectors by employment-weighted averages

<table>
<thead>
<tr>
<th>Industry</th>
<th>Without controls</th>
<th>With controls</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>United States</td>
<td>Sweden</td>
</tr>
<tr>
<td></td>
<td>1984(^a)</td>
<td>1984(^b)</td>
</tr>
<tr>
<td>1. Mining</td>
<td>0.404</td>
<td>0.036</td>
</tr>
<tr>
<td>2. Food, beverages, tobacco</td>
<td>0.094</td>
<td>0.034</td>
</tr>
<tr>
<td>3. Textile, apparel, leather</td>
<td>-0.245</td>
<td>-0.231</td>
</tr>
<tr>
<td>4. Wood</td>
<td>-0.058</td>
<td>-0.163</td>
</tr>
<tr>
<td>5. Paper, printing</td>
<td>0.152</td>
<td>0.100</td>
</tr>
<tr>
<td>6. Chemical</td>
<td>0.272</td>
<td>-0.004</td>
</tr>
<tr>
<td>7. Stone, clay, glass</td>
<td>0.357</td>
<td>-0.009</td>
</tr>
<tr>
<td>8. Basic metals</td>
<td>0.357</td>
<td>0.017</td>
</tr>
<tr>
<td>9. Fabricated metals, machinery</td>
<td>0.274</td>
<td>0.048</td>
</tr>
<tr>
<td>10. Public utilities</td>
<td>0.527</td>
<td>-0.021</td>
</tr>
<tr>
<td>11. Construction</td>
<td>0.216</td>
<td>0.066</td>
</tr>
<tr>
<td>12. Wholesale trade</td>
<td>0.171</td>
<td>0.073</td>
</tr>
<tr>
<td>13. Retail trade</td>
<td>-0.241</td>
<td>-0.097</td>
</tr>
<tr>
<td>14. Restaurants, hotels</td>
<td>-0.504</td>
<td>-0.223</td>
</tr>
<tr>
<td>15. Transport</td>
<td>0.266</td>
<td>0.013</td>
</tr>
<tr>
<td>16. Communication</td>
<td>0.353</td>
<td>0.014</td>
</tr>
<tr>
<td>17. Banking</td>
<td>0.084</td>
<td>0.129</td>
</tr>
<tr>
<td>18. Insurance</td>
<td>0.105</td>
<td>0.048</td>
</tr>
<tr>
<td>19. Business services</td>
<td>0.021</td>
<td>0.181</td>
</tr>
<tr>
<td>20. Social, community services</td>
<td>0.003</td>
<td>-0.024</td>
</tr>
<tr>
<td>21. Recreation, cultural services</td>
<td>-0.181</td>
<td>-0.042</td>
</tr>
<tr>
<td>22. Personal, household services</td>
<td>-0.462</td>
<td>-0.078</td>
</tr>
</tbody>
</table>

Mean of differentials                         | 0.089            | -0.006        | 0.044         | 0.006      |
Mean of differentials in absolute value       | 0.243            | 0.075         | 0.124         | 0.040      |
SD of differentials                           | 0.277            | 0.103         | 0.138         | 0.053      |
Sample size\(^d\)                            | 10.289           | 1,298         | 11,512        | 1,298      |

\(^d\) For both the United States and Sweden, the samples considered include male and female workers.
<table>
<thead>
<tr>
<th>Industry</th>
<th>Australia 1986</th>
<th>Germany 1984</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Agriculture</td>
<td>-0.291</td>
<td>-0.109</td>
</tr>
<tr>
<td>2. Mining, public utilities</td>
<td>0.280</td>
<td>0.113</td>
</tr>
<tr>
<td>3. Manufacturing</td>
<td>0.028</td>
<td>0.032</td>
</tr>
<tr>
<td>4. Construction</td>
<td>0.035</td>
<td>0.044</td>
</tr>
<tr>
<td>5. Trade</td>
<td>-0.057</td>
<td>-0.097</td>
</tr>
<tr>
<td>6. Transport, communication</td>
<td>0.079</td>
<td>-0.019</td>
</tr>
<tr>
<td>7. Finance, business services</td>
<td>0.031</td>
<td>0.014</td>
</tr>
<tr>
<td>8. Public administration</td>
<td>0.063</td>
<td>-0.047</td>
</tr>
<tr>
<td>9. Social, community services</td>
<td>-0.009</td>
<td>-0.098</td>
</tr>
<tr>
<td>10. Recreation, personal services</td>
<td>-0.093</td>
<td>-0.121</td>
</tr>
<tr>
<td>Mean of differentials</td>
<td>0.007</td>
<td>-0.029</td>
</tr>
<tr>
<td>Mean of differentials in absolute value</td>
<td>0.097</td>
<td>0.069</td>
</tr>
<tr>
<td>SD of differentials</td>
<td>0.145</td>
<td>0.079</td>
</tr>
<tr>
<td>Sample size</td>
<td>4.574</td>
<td>2.072</td>
</tr>
</tbody>
</table>


* Source: My results from the SOEP, aggregation of the differentials presented in Section 4.3, Table 4.1. Original estimation method: Heckman’s two-stage estimator. Aggregation by sample employment weights.

* For both Australia and Germany, the samples considered include only male workers.
TABLE 4.C6
Wage differentials for AUSTRALIA and AUSTRIA:
deviations from the employment-weighted mean differential
Aggregation of the original differentials into a common classification
of industry sectors by employment-weighted averages

<table>
<thead>
<tr>
<th>Industry</th>
<th>Australia 1986</th>
<th>Austria 1985</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Agriculture</td>
<td>-0.291</td>
<td>-0.106</td>
</tr>
<tr>
<td>2. Mining</td>
<td>0.440</td>
<td>0.067</td>
</tr>
<tr>
<td>3. Manufacturing</td>
<td>0.028</td>
<td>-0.005</td>
</tr>
<tr>
<td>4. Public utilities</td>
<td>0.161</td>
<td>0.076</td>
</tr>
<tr>
<td>5. Construction</td>
<td>0.035</td>
<td>0.043</td>
</tr>
<tr>
<td>6. Trade</td>
<td>-0.057</td>
<td>-0.021</td>
</tr>
<tr>
<td>7. Transport, communication</td>
<td>0.079</td>
<td>-0.032</td>
</tr>
<tr>
<td>8. Finance, real estate, business</td>
<td>0.031</td>
<td>0.021</td>
</tr>
<tr>
<td>9. Public administration</td>
<td>0.063</td>
<td>-0.027</td>
</tr>
<tr>
<td>10. Social, community services</td>
<td>-0.009</td>
<td>0.024</td>
</tr>
<tr>
<td>11. Recreation, personal services</td>
<td>-0.093</td>
<td>0.018</td>
</tr>
</tbody>
</table>

Mean of differentials
Mean of differentials in absolute value
SD of differentials
Sample size


c For Australia, the sample considered includes only male workers; for Austria, the sample consists of male and female workers.
TABLE 4.C7

Wage differentials for AUSTRALIA and SWEDEN:
deviations from the employment-weighted mean differential
Aggregation of the original differentials into a common classification
of industry sectors by employment-weighted averages

<table>
<thead>
<tr>
<th>Industry</th>
<th>With controls</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Australia 1986</td>
<td>Sweden 1984</td>
<td></td>
</tr>
<tr>
<td>1. Agriculture</td>
<td>-0.219</td>
<td>-0.096</td>
<td></td>
</tr>
<tr>
<td>2. Mining</td>
<td>0.440</td>
<td>0.033</td>
<td></td>
</tr>
<tr>
<td>3. Manufacturing</td>
<td>0.028</td>
<td>0.015</td>
<td></td>
</tr>
<tr>
<td>4. Public utilities</td>
<td>0.161</td>
<td>-0.007</td>
<td></td>
</tr>
<tr>
<td>5. Construction</td>
<td>0.035</td>
<td>0.073</td>
<td></td>
</tr>
<tr>
<td>6. Trade</td>
<td>-0.057</td>
<td>0.020</td>
<td></td>
</tr>
<tr>
<td>7. Transport</td>
<td>0.078</td>
<td>-0.017</td>
<td></td>
</tr>
<tr>
<td>8. Communication</td>
<td>0.080</td>
<td>-0.046</td>
<td></td>
</tr>
<tr>
<td>9. Finance, business services</td>
<td>0.031</td>
<td>0.137</td>
<td></td>
</tr>
<tr>
<td>10. Public administration</td>
<td>0.063</td>
<td>0.011</td>
<td></td>
</tr>
<tr>
<td>11. Social, community services</td>
<td>-0.009</td>
<td>-0.081</td>
<td></td>
</tr>
<tr>
<td>12. Recreation, personal services</td>
<td>-0.093</td>
<td>-0.148</td>
<td></td>
</tr>
<tr>
<td>Mean of differentials</td>
<td>0.039</td>
<td>-0.009</td>
<td></td>
</tr>
<tr>
<td>Mean of differentials in absolute value</td>
<td>0.114</td>
<td>0.057</td>
<td></td>
</tr>
<tr>
<td>SD of differentials</td>
<td>0.170</td>
<td>0.077</td>
<td></td>
</tr>
<tr>
<td>Sample size(^c)</td>
<td>4,574</td>
<td>671</td>
<td></td>
</tr>
</tbody>
</table>

\(^c\) For both Australia and Sweden, the samples considered include only male workers.
TABLE 4.C8
Wage differentials for GERMANY and AUSTRIA: deviations from the employment-weighted mean differential
Aggregation of the original differentials into a common classification of industry sectors by employment-weighted averages

<table>
<thead>
<tr>
<th>Industry</th>
<th>Germany 1984</th>
<th>Austria 1983</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Agriculture</td>
<td>-0.105</td>
<td>-0.106</td>
</tr>
<tr>
<td>2. Mining, public utilities</td>
<td>0.092</td>
<td>0.073</td>
</tr>
<tr>
<td>3. Chemical</td>
<td>0.078</td>
<td>0.085</td>
</tr>
<tr>
<td>4. Stone, clay, glass</td>
<td>-0.011</td>
<td>0.015</td>
</tr>
<tr>
<td>5. Metals, machinery</td>
<td>0.036</td>
<td>0.024</td>
</tr>
<tr>
<td>6. Wood, paper, printing</td>
<td>0.093</td>
<td>-0.021</td>
</tr>
<tr>
<td>7. Textile, apparel</td>
<td>-0.102</td>
<td>-0.098</td>
</tr>
<tr>
<td>8. Food, beverages, tobacco</td>
<td>-0.089</td>
<td>-0.033</td>
</tr>
<tr>
<td>9. Construction</td>
<td>0.070</td>
<td>0.043</td>
</tr>
<tr>
<td>10. Trade</td>
<td>-0.076</td>
<td>-0.030</td>
</tr>
<tr>
<td>11. Transport, communication</td>
<td>-0.019</td>
<td>-0.032</td>
</tr>
<tr>
<td>12. Banking, insurance</td>
<td>-0.011</td>
<td>0.024</td>
</tr>
<tr>
<td>13. Personal, household services</td>
<td>-0.080</td>
<td>-0.017</td>
</tr>
<tr>
<td>14. Recreation, cultural services</td>
<td>0.060</td>
<td>0.058</td>
</tr>
<tr>
<td>15. Health, social services</td>
<td>-0.032</td>
<td>0.023</td>
</tr>
<tr>
<td>16. Business services</td>
<td>0.063</td>
<td>0.016</td>
</tr>
<tr>
<td>17. Public administration</td>
<td>-0.021</td>
<td>-0.027</td>
</tr>
</tbody>
</table>

Mean of differentials               | -0.003       | -0.000       |
Mean of differentials in absolute value | 0.061       | 0.043        |
SD of differentials                  | 0.071        | 0.053        |
Sample size                         | 4,389        | 11,829       |

* Source: my results from the SOEP, aggregation of the differentials presented in this Appendix. Table 4.C2. Original estimation method: OLS. Aggregation by sample employment weights.


c For both Germany and Austria, the samples considered include male and female workers.
TABLE 4.C9
Wage differentials for GERMANY and SWEDEN:
deviations from the employment-weighted mean differential
Aggregation of the original differentials into a common classification
of industry sectors by employment-weighted averages

<table>
<thead>
<tr>
<th>Industry</th>
<th>Without controls</th>
<th></th>
<th>With controls</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Germany 1984*</td>
<td>Sweden 1984*</td>
<td>Germany 1984*</td>
</tr>
<tr>
<td>1. Agriculture</td>
<td>-0.204</td>
<td>-0.149</td>
<td>-0.105</td>
</tr>
<tr>
<td>2. Mining, public utilities</td>
<td>0.209</td>
<td>0.031</td>
<td>0.092</td>
</tr>
<tr>
<td>3. Chemical</td>
<td>0.127</td>
<td>-0.004</td>
<td>0.078</td>
</tr>
<tr>
<td>4. Stone, clay, glass</td>
<td>0.026</td>
<td>-0.009</td>
<td>-0.011</td>
</tr>
<tr>
<td>5. Basic metals</td>
<td>0.030</td>
<td>0.017</td>
<td>0.023</td>
</tr>
<tr>
<td>6. Machinery</td>
<td>0.098</td>
<td>0.048</td>
<td>0.044</td>
</tr>
<tr>
<td>7. Wood, paper, printing</td>
<td>0.035</td>
<td>-0.000</td>
<td>0.093</td>
</tr>
<tr>
<td>8. Textile, apparel</td>
<td>-0.216</td>
<td>-0.231</td>
<td>-0.102</td>
</tr>
<tr>
<td>9. Food, beverages, tobacco</td>
<td>-0.172</td>
<td>0.034</td>
<td>-0.089</td>
</tr>
<tr>
<td>10. Construction</td>
<td>0.086</td>
<td>0.066</td>
<td>0.070</td>
</tr>
<tr>
<td>11. Wholesale trade</td>
<td>-0.008</td>
<td>0.073</td>
<td>-0.002</td>
</tr>
<tr>
<td>12. Retail trade</td>
<td>-0.247</td>
<td>-0.097</td>
<td>-0.101</td>
</tr>
<tr>
<td>13. Transport, communication</td>
<td>0.036</td>
<td>0.013</td>
<td>-0.019</td>
</tr>
<tr>
<td>14. Banking</td>
<td>0.128</td>
<td>0.129</td>
<td>-0.047</td>
</tr>
<tr>
<td>15. Insurance</td>
<td>0.185</td>
<td>0.048</td>
<td>0.062</td>
</tr>
<tr>
<td>16. Personal, household services</td>
<td>-0.224</td>
<td>-0.139</td>
<td>-0.080</td>
</tr>
<tr>
<td>17. Recreation, cultural services</td>
<td>0.167</td>
<td>-0.042</td>
<td>0.060</td>
</tr>
<tr>
<td>18. Health, social services</td>
<td>-0.021</td>
<td>-0.024</td>
<td>-0.032</td>
</tr>
<tr>
<td>19. Business services</td>
<td>0.074</td>
<td>0.181</td>
<td>0.063</td>
</tr>
<tr>
<td>20. Public administration</td>
<td>0.047</td>
<td>0.048</td>
<td>-0.021</td>
</tr>
</tbody>
</table>

Mean of differentials            | 0.008            | -0.000                    | -0.001            | 0.005            |
Mean of differentials in absolute value| 0.117            | 0.069                     | 0.060             | 0.040            |
SD of differentials              | 0.144            | 0.096                     | 0.070             | 0.053            |
Sample size                      | 4,389            | 1,298                     | 4,389             | 1,298            |

* Source: my results from the SOEP, aggregation of the differentials presented in this Appendix, Table 4.C2. Original estimation method: OLS. Aggregation by sample employment weights.


c For both Germany and Sweden, the samples considered include male and female workers.
TABLE 4.C10
Wage differentials for AUSTRIA and SWEDEN:
deviations from the employment-weighted mean differential
Aggregation of the original differentials into a common classification
of industry sectors by employment-weighted averages

<table>
<thead>
<tr>
<th>Industry</th>
<th>Austria 1983</th>
<th>Sweden 1984</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Agriculture</td>
<td>-0.106</td>
<td>-0.061</td>
</tr>
<tr>
<td>2. Public utilities</td>
<td>0.076</td>
<td>0.006</td>
</tr>
<tr>
<td>3. Mining</td>
<td>0.067</td>
<td>0.023</td>
</tr>
<tr>
<td>4. Food, beverages, tobacco</td>
<td>-0.033</td>
<td>0.020</td>
</tr>
<tr>
<td>5. Textile, apparel, leather</td>
<td>-0.098</td>
<td>-0.074</td>
</tr>
<tr>
<td>6. Wood</td>
<td>-0.067</td>
<td>-0.072</td>
</tr>
<tr>
<td>7. Paper, printing</td>
<td>0.068</td>
<td>0.063</td>
</tr>
<tr>
<td>8. Chemical</td>
<td>0.085</td>
<td>0.054</td>
</tr>
<tr>
<td>9. Stone, clay, glass</td>
<td>0.015</td>
<td>0.008</td>
</tr>
<tr>
<td>10. Metals, machinery</td>
<td>0.024</td>
<td>0.021</td>
</tr>
<tr>
<td>11. Construction</td>
<td>0.043</td>
<td>0.069</td>
</tr>
<tr>
<td>12. Trade</td>
<td>-0.030</td>
<td>-0.015</td>
</tr>
<tr>
<td>13. Restaurants, hotels</td>
<td>0.018</td>
<td>-0.021</td>
</tr>
<tr>
<td>14. Transport, communication</td>
<td>-0.032</td>
<td>0.008</td>
</tr>
<tr>
<td>15. Banking, insurance</td>
<td>0.024</td>
<td>0.032</td>
</tr>
<tr>
<td>16. Real estate, business services</td>
<td>0.016</td>
<td>0.099</td>
</tr>
<tr>
<td>17. Sanitary services</td>
<td>-0.106</td>
<td>-0.002</td>
</tr>
<tr>
<td>18. Recreation, cultural services</td>
<td>0.050</td>
<td>-0.127</td>
</tr>
<tr>
<td>19. Social, community services</td>
<td>0.040</td>
<td>-0.030</td>
</tr>
<tr>
<td>20. Public administration</td>
<td>-0.027</td>
<td>0.028</td>
</tr>
<tr>
<td>21. Personal, household services</td>
<td>-0.001</td>
<td>-0.004</td>
</tr>
</tbody>
</table>

Mean of differentials: 0.001
Mean of differentials in absolute value: 0.049
SD of differentials: 0.059
Sample size: 11,829


For both Austria and Sweden, the samples considered include male and female workers.
FIGURE 4.C1

Industry wage differentials estimated with controls: UNITED STATES and AUSTRALIA
FIGURE 4.C2.1
Industry wage differentials estimated without controls: UNITED STATES and GERMANY

FIGURE 4.C2.2
Industry wage differentials estimated with controls: UNITED STATES and GERMANY
FIGURE 4.C3

Industry wage differentials estimated with controls: UNITED STATES and AUSTRIA
FIGURE 4.C4.1
Industry wage differentials estimated without controls: UNITED STATES and SWEDEN

FIGURE 4.C4.2
Industry wage differentials estimated with controls: UNITED STATES and SWEDEN
FIGURE 4.C5

Industry wage differentials estimated with controls: AUSTRALIA and GERMANY

Australia

Germany

-0.4 -0.1 0 0.1 0.2 0.3

-0.14 -0.1 -0.06 -0.02 0.02 0.06 0.1
FIGURE 4.C6
Industry wage differentials estimated with controls: AUSTRALIA and AUSTRIA
FIGURE 4.C7

Industry wage differentials estimated with controls: AUSTRALIA and SWEDEN

Australia

Sweden
FIGURE 4.C8

Industry wage differentials estimated with controls: GERMANY and AUSTRIA

Wood, paper, printing
Business services
Construction
Recreation, cultural services
Metal machinery
Chemical
Mining, public utilities
Transport, communication
Public administration
Health, social services
Trade
Personal, household services
Agriculture
Food, beverages, tobacco
FIGURE 4.C9.1

Industry wage differentials estimated without controls: GERMANY and SWEDEN

FIGURE 4.C9.2

Industry wage differentials estimated with controls: GERMANY and SWEDEN
FIGURE 4.C10
Industry wage differentials estimated with controls: AUSTRIA and SWEDEN
References


Chapter 5

Cross-Country Comparisons of the Inter-Industry Wage Structure: Empirical Evidence for the U.S., Canada, Australia, Germany and the Netherlands with the "Luxembourg Income Study" Data-Bank

5.1 Introduction

In Chapter 4, I have presented some empirical evidence for the inter-industry wage structures of various countries. This evidence is based on individual data in a regression approach and shows the existence of significant differences across countries. Among non-competitive forces in wage determination, institutional conditions of wage bargaining, and in particular the degree of centralization, seem to play a relevant role in explaining the observed pattern of inter-industry wage differentials across countries, as suggested by the theoretical considerations illustrated in Chapter 2. These results are in contrast with what emerges from the type of evidence based on aggregate data that I have discussed earlier in Chapter 3.

The present Chapter will provide additional evidence concerning the same issue, in order to verify the degree of generality of the conclusions reached in Chapter 4. The empirical analysis proposed here relies on an approach which is different from that adopted in Chapter 4 and which tries to overcome some of the difficulties met in that context. For this purpose it employs a different data source, the "Luxembourg Income Study" (LIS) data-bank.

Cross-country comparisons that utilize studies made by various authors confront certain limitations. The degree of comparability of the results is affected by several
differences in the definition of the samples of interest and of the dependent and explanatory variables, as well as in the statistical methodology applied for the estimation of the models. Moreover, the comparisons are made essentially through simple correlations between the vectors of estimated wage differentials appearing in the various papers, aggregated for this purpose into a common set of industries. Little information is usually provided about other aspects of the estimation procedure - like the choice of base groups in the definition of control dummy variables, the treatment of missing data, and sometimes even the values of the estimated coefficients for human capital controls - and the reader has no access to some of the statistical results - like the variance-covariance matrix of estimated coefficients. This, as a matter of fact, limits the possibility of a statistical comparison between estimated inter-industry wage structures to the calculation of correlation coefficients.

The empirical analysis in this Chapter employs a different strategy, which can be regarded as complementary to that applied in the previous Chapter 4. The "Luxembourg Income Study" data-bank is a collection of micro data-sets for several countries that can be indirectly accessed through the electronic mail system and processed with the statistical package SPSS-X. On the one hand, the use of a single data source for various national data-sets partly reduces the above-mentioned problems of heterogeneity, because it permits, to a certain extent, a control of the differences affecting the reliability of cross-country comparisons. Besides, the direct estimate of the wage regression models for the different countries gives the possibility of employing all the statistical results produced by the estimation procedure. In particular, the availability of the variance-covariance matrices of estimated coefficients permits the construction of a test for cross-country equality restrictions on inter-industry wage structures. This test, based on the method of minimum distance estimation, provides a criterion to evaluate the hypothesis of similarity among countries which is an alternative to simple correlation coefficients. The minimum distance $\chi^2$ test makes recognition of the fact that industry wage differentials for each country are estimates of population parameters subject to a sampling error and are therefore associated with measures of the precision of the estimate (the OLS standard errors), which are otherwise ignored in the calculation of correlation coefficients. On the other hand, however, the nature of the data source, the desire to examine various countries, and the necessity to obtain sufficiently comparable results make the approach adopted in this Chapter less accurate than the one used in Chapter 4 for the German case and in the other authors’ studies considered in Chapter 4.
The number of control variables for human capital characteristics, socio-demographic aspects, and working conditions that can be constructed is considerably smaller. Industry affiliation of workers is defined according to a much less detailed classification of sectors. The statistical method that can be applied to estimate wage equations is limited to ordinary least squares by the package SPSS-X. Several other features concerning the selection of the sub-samples of interest and the construction of variables, that could be taken into account having direct access to the original data sources, are here ignored. In this respect, the estimates obtained in Chapter 4 are more satisfactory and, therefore, should be evaluated together with the results given in the present Chapter.

The rest of the Chapter is structured as follows. Section 5.2 assesses the "Luxembourg Income Study" database and describes the country data-sets used, the characteristics of the sub-samples of interest, and the specification of the estimated wage equations. Section 5.3 presents and discusses the main results of my regression analyses based on LIS data for the countries considered: the United States, Canada, Australia, Germany, and the Netherlands. Section 5.4 compares the inter-industry wage structures of the various countries by means of correlation coefficients and minimum distance $\chi^2$ tests. Section 5.5 contains some concluding remarks.

5.2 Empirical Evidence: Data, Sub-Samples, and Variables

5.2.1 The "Luxembourg Income Study" (LIS) Data-Bank

The "Luxembourg Income Study"42 (LIS) data-bank is a collection of separate data-sets characterized by two main aspects: they contain cross-sectional observations at the individual level and consist of nationwide representative samples for a variety of different countries. One or more distinct data-sets are available for each of the countries that choose to participate in the project. At the beginning of 1994, the LIS database covered 14 countries: Australia, Canada, Germany, Israel, the Netherlands, Norway, Sweden, Switzerland, the

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42 The "Luxembourg Income Study" was initially created with the financial support of the Ford Foundation and subsequently funded by an international consortium of science foundations, research councils and centres, and government agencies in member countries. Researchers in member states may use the LIS database at no charge, but exclusively for scientific purposes.
United Kingdom, the United States, France, Poland, Italy, and Luxembourg. Further expansions have been planned for a rather long time, but have not yet been completed. They should lead to the inclusion of Austria, Denmark, Finland, Ireland, Belgium, Greece, New Zealand, Spain, Japan, and Hungary, and of more recent data for the already existing countries. At present, for each country, there are from 1 to 4 cross-sectional data-sets for different years, the most recent of which refers to one of the years within the period 1985-87 for almost all LIS countries.

The LIS data-bank is physically resident on an IBM 4381 computer at the Government's computer center of the Grand Duchy of Luxembourg and can be utilized through the service supplied by the Center for Population, Poverty, and Policy Studies (CEPS). The data contained in the LIS database are not accessible directly and cannot be copied or otherwise removed. Access is provided through the LIS system interface and the SPSS-X statistical package. This procedure is required in order to meet privacy and confidentiality restrictions imposed on the release of data by national statistical agencies of some of the LIS member countries. In practice, the data-bank can be reached through the international electronic mail system (EARN/BITNET network). Users can send to Luxembourg, via electronic mail, files containing properly formatted sequences of SPSS-X commands, which are reviewed and executed by the LIS technical staff. Output from SPSS-X programs is sent back to the user (usually after 1-2 days) again via electronic mail. This approach represents a serious limitation to the possibility of exploiting a potentially rich data source: researchers have only indirect access to the data and, as a result, they are restricted to the use of SPSS-X. This package does not represent the most suitable option for certain purposes, like the treatment of limited-dependent and qualitative variables models which require maximum likelihood estimation techniques commonly employed in microeconometrics.

43 For example, the inclusion of a Hungarian data-set had been announced in 1989, but the data were not yet available at the time of writing this Chapter.

44 At the time of writing this Chapter, SPSS-X Version 4 was in use.

45 Although electronic mail is certainly the most convenient system to work with the LIS data, there are in fact two other ways to use the database. The first alternative is to post data requests (in disk form) and receive the program output by mail. This however increases the time frame to at least two weeks for each request. The second possibility consists in spending a certain period at the CEPS Center in Luxembourg, working with the LIS staff and preparing SPSS-X data requests under their supervision.
However this constraint does not set a crucial limit to the present analysis, which is essentially based on ordinary least squares estimation.

The content of the LIS data-sets has been derived directly from household surveys and/or administrative records from the various countries. Data for the individual survey units have been sent to Luxembourg, where they have been transformed into a "LIS format" by the LIS administrators, and then loaded into the database. The LIS data-sets are accessible on both a household basis, and on a person basis. The process of transformation of data into "LIS format" is not very clear in its purposes and implications. In principle, it should lead to a higher degree of comparability between variables of different countries. As a matter of fact, it implies a certain amount of loss of information originally contained in the data. This point can be verified with reference to the case of Germany. As we will see in Sub-Section 5.2.2, the original survey source of the German data-set loaded into the LIS database is the Socio-Economic Panel (SOEP), the same data source used for my analysis in Chapter 4 and on which I have, therefore, direct control. The original variable for schooling, for example, has been re-codified by the LIS administrators and the number of qualifications reduced. A separate variable for education received in the country of origin by foreign residents has been completely eliminated, although this variable is quite useful to capture specific aspects of human capital formation - as proved by the results obtained in Chapter 4. The need for such a transformation of the original data is not totally evident: it involves a reduction of accuracy and does not improve comparability with other countries in a clear way.

A single, standard set of SPSS-X variable names is used to define the variables for all countries. This, again, is done by the LIS administrators in the attempt to increase data comparability and to permit cross-country analyses. In the case of some monetary variables, when their content is adjusted accordingly, this can represent an advantage for comparative studies. For example, all income amounts refer to a calendar year. However, there is an

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46 The original SOEP schooling variable can assume 6 alternative values for short-course secondary school, intermediate type of secondary school, technical high school, academically-oriented secondary school, other schooling, or no type of schooling completed. The LIS schooling variable for Germany can assume only 5 values for elementary school, vocational school, technical high school, general high school, or other education. In both cases, missing values are in a further category.

47 It should be noted, however, that in some cases this is obtained just by annualizing to a 12-month accounting period income amounts which originally referred to a different time period (e.g. weekly or monthly data multiplied by 52 or 12 respectively). In such cases the gain in terms of "comparability" is rather arguable! The issue can be illustrated again with reference to Germany. The original SOEP variable for individual gross
obvious trade-off between the number of variables that have been maintained in the LIS data-sets and the number of countries considered. Data surveys that are originally very detailed experience a drastic contraction, if the set of variables included in the LIS database is limited by the condition of being the same for all countries. The German case can serve again as a good example of this problem. Of the original variables at the person level in the second wave of the SOEP, that are more that 750, only 25 have been maintained in the LIS data-set for Germany.

The data for each country is stored as an independent table within a relational database system. Consequently, the meaning of the specific values assumed by any one categorical variable may differ across countries. This obviously reflects diversities in country-specific aspects, as well as in the purposes and designs of the various national surveys. When comparisons between different countries are made, it is, therefore, necessary to be extremely careful about the actual content of the variables treated. The material presented in Appendix 5.A to the present Chapter provides an indication of the type of data analysis required to define a set of relatively homogeneous controls even for a limited number of countries. For example, the variable for the individuals' level of education is codified with the same name for all countries (PEDUC). But the content of this variable is quite different for the various countries, as can be seen from the lists given in Appendix 5.A. In some cases (e.g. Australia and Germany), the values assumed by this variable correspond to educational qualifications and completed levels of schooling. In other cases (e.g. the Netherlands), the same values indicate attendance to courses not necessarily completed. In others (e.g. the United States and Canada), these values correspond to years of schooling or to a mixture of educational qualifications and years of schooling. In any case, the discrete set of possible values assumed by the education variable is different for every country and equal values may correspond to different schooling levels (e.g. the value 4 of the variable PEDUC indicates 3 years of education for the United States, 12 years of education for Canada, and a completed general high school degree for Germany). This heterogeneity clearly reflects institutional aspects of the educational systems of the various countries and different surveying methods in each country.

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earnings refers to the month preceding that of the interview. The corresponding LIS variable for gross annual wage/salary is calculated by the LIS administrators multiplying the SOEP variable by 12. Detailed information on this point is unfortunately not available for all the countries in the data-bank and this can potentially affect the actual degree of data comparability across countries. I shall return on this problem later in Sub-Section 5.2.4.
survey. The same type of considerations applies to the variable for the individuals' occupation (POCC). With respect to education and occupation, therefore, the attempt to make national data-sets comparable reduces to the fact of giving the same name to the corresponding variables.

To summarize, the aim of considering a large number of countries can be attained only at the cost of a sometimes heavy reduction in accuracy. In my study of the international wage structure, however, I exploit what is certainly a positive feature of the LIS data-bank, that of providing information for several countries through a single data source. This permits cross-country comparative analyses that would otherwise be extremely demanding in terms of computing resources and availability of data.

5.2.2 The Country Data-Sets Used

The limitations imposed in practice by the structure of the LIS database become immediately evident in the process of selecting as many countries as possible for my econometric study. In order to perform a cross-country analysis, I have to face a problem of comparability of data and results. This problem is dealt with in three stages, the first of which consists in choosing among the LIS national data-sets those that contain the basic variables needed for my regression model. The second stage is represented by the selection of sub-samples of units which are as similar as possible and will be illustrated in Sub-Section 5.2.3. The third stage consists in the construction of the variables entering the model specification and will be presented in the following Sub-Section 5.2.4. As we will see, of the 14 countries originally included in the LIS data-bank only a small number can actually be employed in my empirical investigation.

Although the units of reference of the original surveys are households for all the countries, the LIS data-sets are accessible at both a household level, and at a person level. Only the latter type of units is relevant for the present study. Person records are not available for all the data-sets relative to different years, but only for the LIS second wave data-sets. I am, therefore, bound to consider only these data, but this does not imply per se the exclusion of any of the 14 countries: they are all present with a second wave and have some person level data in that data-set. Problems arise when considering the appropriate variables for my econometric analysis. The regression model used to estimate inter-industry wage differentials
obviously requires a variable for industry affiliation of workers and a measure of their wage rate. The first condition leads to the exclusion of Israel, Norway, Switzerland, France, and Luxembourg. The wage rate dependent variable is defined as an hourly wage, which involves a measure of the total wage and a measure of hours of work. The total wage variable is not available for Italy and Poland, while the variable for hours worked is missing in the case of Sweden. Moreover, as illustrated in Chapter 2, one of the theoretical foundations of my wage regression model is human capital theory. This implies the inclusion of human capital controls as explanatory variables and, among these, the level of education is certainly an essential one. The lack of a variable for education implies the final exclusion of the United Kingdom. The large number of countries that cannot be taken into account provides clear evidence of the limitations to the actual comparability of LIS data-sets. Variables that are crucial for the present study may not be of primary interest according to the various purposes of the original surveys and are often missing in the database.

In my empirical investigation then, I can consider only one cross-sectional wave and only five countries: the United States, Canada, Australia, Germany, and the Netherlands. This limited amount of cases, however, does not represent an absolute obstacle for the main purpose of my analysis, that of comparing the inter-industry wage structures of countries characterized by different institutional conditions for wage bargaining. As we have seen in Chapter 2, these five countries cover a sufficiently wide range of different types of bargaining procedures: the United States and Canada present an extremely decentralized system of wage bargaining, Australia and Germany represent intermediate cases, and the Netherlands has one of the highest degrees of centralization of wage bargaining among Western countries.

The main characteristics of the country data-sets considered are the following:

*United States*
Original survey source: *March Current Population Survey (CPS)*.
Main purpose of the survey: to provide estimates of employment, unemployment, and other characteristics of the labour force.
Original sample size: 11,614 households (the LIS data-set is a 20% random sample of the full data-set); 24,964 individuals.
b) Canada
Original survey source: *Survey of Consumer Finances*.
Main purpose of the survey: to measure earnings levels, and the composition and distribution of income.
Original sample size: 11,518 households (the LIS data-set is a 33% random sample of the full data-set); 24,412 individuals.

c) Australia
Original survey source: *Income Distribution Survey*.
Main purpose of the survey: to collect information on working arrangements, incomes, and housing costs.
Original sample size: 7,563 households (the LIS data-set coincides with the full data-set); 16,364 individuals.

d) Germany
Original survey source: *Socio-Economic Panel (SOEP): Wave 2*.
Main purpose of the survey: to provide micro-analyses of the dynamics of individual welfare, and to evaluate the social impact of government social policy.
Original sample size: 5,174 households (the LIS data-set coincides with the full data-set); 11,282 individuals.

e) Netherlands
Original survey source: *Additional Enquiry on the Use of (Public) Services (AVO)*.
Main purpose of the survey: to measure income, household composition, and the use of public services, like education, health care, housing, social and cultural activities.
Original sample size: 6,771 households (the LIS data-set coincides with the full data-set); 8,287 individuals.
As we can see from this list, the original surveys differ to a certain extent in their purposes and in the cases of the United States and Canada they are only partially represented by the corresponding LIS data-sets. The LIS data-set for the United States has been derived from the same survey source utilized by Krueger and Summers (1988) in their previously cited study of the inter-industry wage structure, but it refers to a different year (1986 instead of 1984). The LIS data-set for Australia exactly coincides with the survey data used by Borland and Suen (1990) in the study that I considered in Chapter 4 for cross-country comparisons. The LIS data-set for Germany relies on the same data source utilized in the analysis of the German case that I presented in Chapter 4, with the difference of referring to the second rather than the first wave of the panel. As already mentioned in Sub-Section 5.2.1, the transformation of variables in "LIS format" and the definition of a common set of variables for all countries implies a loss of information with respect to the original surveys. The empirical approach adopted in this Chapter is substantially similar to that used by Krueger and Summers, Borland and Suen, and in Chapter 4. However, the restrictions imposed by the LIS database give rise to a certain amount of relevant differences, with respect to those studies, that make the present analysis less accurate.

5.2.3 Sub-Samples Characteristics

The second stage in dealing with the problem of cross-country comparability is represented by the selection of the sub-samples actually used in my regression analysis. One of the difficulties encountered in the comparative study of Chapter 4 was the heterogeneity of the samples selected by the various authors for their empirical investigations. The most evident difference is probably the use of a sample of both male and female individuals in some cases (e.g. the United States and Austria) and of a sample of male individuals only in others (e.g. Australia)\(^{48}\). This and other dissimilarities possibly affect the final regression results, leading to a diversified pattern of inter-industry wage structures across countries which may be only illusory.

\(^{48}\) For Germany and Sweden, results from both types of samples (males+females and males only) are available and used in Chapter 4. However, the two sets of results - at least in the case of Germany - were obtained from rather different econometric models, thus inducing another kind of dissimilarity.
With the LIS data-bank I can directly control the main aspects related to the selection of the samples of interest, in all the countries considered. The sub-samples are defined according to criteria which reflect the specific nature of my econometric model and are as systematic as possible across the various countries. Differences among countries in the content of LIS variables having the same names, as explained previously in Sub-Section 5.2.1, may affect the actual degree of comparability between sub-samples. Appendix 5.A illustrates all the variables involved in the selection procedure and lists the choices made for each country. Clearly, a complete identity of the selected samples cannot be achieved. However, I exploit all the information available in the attempt to define sets of individual units that are relatively homogeneous, especially if compared with those underlying the analysis proposed in Chapter 4.

The sub-sample selection criteria for each country are reported in the following lists and discussed afterwards in terms of their general objectives and effects. Appendix 5.B provides a full description of the number of observations remaining in the samples after each selection.

a) United States

i) male individuals;

ii) individuals 15 years old or older;

iii) employees currently employed, excluding unemployed workers, students, ill disabled, and other individuals not in the labour force;

iv) private and public wage and salary employees, excluding self-employed individuals, unpaid workers, and Government employees (who include military personnel, judges, etc.);

v) regular full-time or part-time workers, employed for the whole year of reference (52 weeks per year);

vi) workers who do not report missing values for the wage variable and/or the hours worked variable;

vii) workers who report an hourly wage rate greater than 1 US$ and less than or equal to 250 US$.

The initial sample of all male individuals contains 11,837 observations. This series of selections lead to a final sub-sample of 4,400 observations (about 37% of the initial sample).
b) Canada

i) male individuals;

ii) individuals 15 years old or older;

iii) employees currently employed, excluding unemployed workers and other individuals not in the labour force;

iv) private and public wage and salary employees, excluding self-employed individuals and unpaid family workers;

v) regular full-time or part-time workers, employed for the whole year of reference (52 weeks per year);

vi) workers who do not report missing values for the wage variable and/or the hours worked variable;

vii) workers who report an hourly wage rate greater than 1 Can$ and less than or equal to 320 Can$.

The initial sample of all male individuals contains 11,977 observations. This series of selections lead to a final sub-sample of 5,000 observations (about 42% of the initial sample).

c) Australia

i) male individuals;

ii) individuals 15 years old or older;

iii) employees full-time or part-time employed, excluding permanently disabled individuals, students, unpaid voluntary workers, unemployed workers, and other individuals not in the labour force;

iv) private and public wage and salary employees, excluding self-employed individuals, family workers, and military personnel;

v) regular full-time or part-time workers, employed for the whole year of reference (52 weeks per year);

vi) workers who do not report missing values for the wage variable and/or the hours worked variable;

vii) workers who report an hourly wage rate greater than 1 Aus$ and less than or equal to 365 Aus$.

The initial sample of all male individuals contains 8,142 observations. This series of selections lead to a final sub-sample of 3,543 observations (about 44% of the initial sample).
d) Germany

i) male individuals;

ii) individuals 15 years old or older:

iii) private and public employees currently employed, excluding individuals not in the labour force, unemployed workers, students, and military personnel:

iv) wage and salary employees, excluding professionals, self-employed workers, trainees, and civil servants qualified as Beamten, who being public officials are subject to peculiar regulations affecting their position in the labour market;

v) regular full-time or part-time workers, employed for the whole year of reference (52 weeks per year);

vi) workers who do not report missing values for the wage variable and/or the hours worked variable;

vii) workers who report an hourly wage rate greater than 1 DM and less than or equal to 400 DM.

The initial sample of all male individuals contains 5,573 observations. This series of selections lead to a final sub-sample of 2,447 observations (about 44% of the initial sample).

e) Netherlands

i) male individuals;

ii) individuals 15 years old or older;

iii) employees in the labour force, excluding unemployed workers, students, and other individuals not in the labour force;

iv) private and public wage and salary employees, excluding self-employed individuals and unpaid family workers;

v) regular full-time or part-time workers, who have not received unemployment benefits in the period of reference and, therefore, have been employed for the whole year of reference;

vi) workers who do not report missing values for the wage variable and/or the hours worked variable;

vii) workers who report an hourly wage rate greater than 1 Fl and less than or equal to 445 Fl.

The initial sample of all male individuals contains 4,045 observations. This series of selections lead to a final sub-sample of 2,084 observations (about 52% of the initial sample).
Some general remarks about the selection criteria. Firstly, following the approach already chosen in Chapter 4 and justified in Chapter 2, I decide to concentrate on a sample of male workers only, to avoid the problem of self-selection connected with female labour supply. This problem is not otherwise solvable given the indirect nature of the access to the LIS database. The SPSS-X package does not allow for the estimation of sample-selection models and, as mentioned earlier, the data are not transferable from their original location. Furthermore, the wage structure for male and female workers tends to be quite different in all countries and a separate treatment of the two sub-samples seems, therefore, more correct. Secondly, I consider only regular wage and salary workers, since the focus of the present study is on the institutional conditions characterizing the procedure of wage bargaining between employers and their employees. For this reason I exclude self-employed workers from the sub-samples of all countries. In principle it would be appropriate to eliminate also government and defence workers, who being public officials are subject to special rules affecting the relationship with their employer. Unfortunately this is possible only in the case of the United States, of Germany, and partly of Australia, while for Canada and the Netherlands these categories are not identifiable through the LIS variables. Other classes of civil servants are instead included in all samples in order to take into account public employment, which has a relevant institutional role in the general process of wage determination especially in some of the countries considered. Thirdly, the selection of workers who are employed, either full- or part-time, for the whole year of reference is necessary for the construction of the dependent variable in the regression model: the hourly wage rate. As it will be shown later in Sub-Section 5.2.4, for the calculation of this variable I use the LIS variables for annual earnings and weekly hours of work. To make these two measures mutually comparable I have to restrict my analysis to the workers who have been employed for all the weeks of the reference year and who have not switched, during this period, from full-time to part-time work or vice versa⁴⁹. Fourthly, workers for whom information on

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⁴⁹ The frequencies of full-time and part-time employment in each sub-sample are the following:

<table>
<thead>
<tr>
<th></th>
<th>Full-time (%)</th>
<th>Part-time (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States</td>
<td>94.00</td>
<td>6.00</td>
</tr>
<tr>
<td>Canada</td>
<td>95.46</td>
<td>4.54</td>
</tr>
<tr>
<td>Australia</td>
<td>97.88</td>
<td>2.12</td>
</tr>
<tr>
<td>Germany</td>
<td>99.59</td>
<td>0.41</td>
</tr>
<tr>
<td>Netherlands</td>
<td>n.a.</td>
<td>n.a.</td>
</tr>
</tbody>
</table>
annual earnings and/or weekly hours of work is missing in the original surveys are excluded to permit the construction of the dependent hourly wage variable. The number of cases falling in these categories is given, for each country, in Appendix 5.B. Finally, workers who report an hourly wage rate smaller or greater than the limits indicated for each country are considered to be outliers and eliminated from the sub-samples. Again, the exact incidence of these cases can be found in Appendix 5.B. After all the previous selections are made, percentages of outliers are indeed very small in all samples, ranging from 0.1% for the Netherlands to 1% for Canada.

5.2.4 Estimated Wage Equations: Model Specification and Variables Definition

The specification of the estimated wage equations is based on the standard earnings functions of human capital theory (Becker, 1967; Mincer, 1974), enriched with controls for socio-demographic conditions which may affect the marginal value of investments in human capital, and with a set of dummy variables for industry affiliation of individual workers. This type of specification has been extensively discussed in Chapter 2.

The third stage in the treatment of the issue of data and results comparability across countries consists in the definition of the variables entering the regression model specification. A major limitation faced in the comparisons of Chapter 4 is represented by several differences in the definition of both the dependent variable and particularly of the explanatory variables used in the various national studies of the inter-industry wage structure. With respect to the problem of unobservable labour quality mentioned in Chapter 2, the fact of employing different amounts and types of controls for human capital characteristics, socio-demographic aspects, and working conditions may induce an upward bias in the estimates of industry dummies coefficients which varies in size across countries. This in turn may lead to cross-country dissimilarities in the estimated inter-industry wage structures that are not due to real differences in the competitive and non-competitive factors entering the process of wage determination, but only to a measurement problem.

For the Netherlands, differently from the other countries, information on full-/part-time work is not available. The restriction to full-year employment is, therefore, imposed indirectly through the amount of unemployment benefits received in the reference year, required to be equal to zero.
Comparability is here considered under three aspects: the first refers to the construction of the dependent variable; the second involves the design of human capital and socio-demographic controls; the third concerns the results of my regression analysis in terms of estimated wage differentials and affects the definition of dummy variables for industry affiliation.

For all the countries considered, the dependent variable in the regression model is the logarithm of the individual standard hourly wage. To construct this variable, I use two other variables provided by the LIS data-bank: gross annual wage/salary in the survey reference year and hours worked per week\(^{50}\). The gross annual wage/salary variable, like all LIS income amounts, refers to a calendar year or is annualized to a 12-month accounting period, but it is originally surveyed in different ways in the various countries. In some cases (e.g. Australia), it refers to total annual earnings in the reference year and the interview actually takes place in the following year. In other cases (e.g. Germany), it refers in fact to monthly earnings in the month preceding that of the interview (here the reference year coincides with the year of the interview), which are later multiplied by 12 by the LIS administrators. Hours worked per week are normal (contractual) or average (actual) weekly hours worked in the year or in the month of reference. Detailed information on these issues is unfortunately not available for all the countries considered in the present study. Differences in survey criteria may, therefore, affect the degree of comparability of the dependent variable across countries. The hourly wage variable is then constructed as gross annual wage/salary divided by 52 times the number of hours worked per week. As already said, individuals who report missing values for gross wage/salary and/or hours worked are eliminated from the sub-samples.

\(^{50}\) For Australia, differently from the other countries, hours worked per week are not represented by a continuous variable, but are grouped in 9 classes in the following way:

1 = less than 10 hours  
2 = between 10 and 19 hours  
3 = between 20 and 24 hours  
4 = between 25 and 29 hours  
5 = between 30 and 34 hours  
6 = between 35 and 39 hours  
7 = between 40 and 44 hours  
8 = between 45 and 49 hours  
9 = 50 hours or more.

For the classes 1 and 9 I have assigned the values 5 and 55, respectively, to the variable “weekly hours worked” actually used in the construction of hourly wages. For the other classes I have considered the mid-point of each class.
As far as the choice of human capital and socio-demographic controls is concerned, I tried to define a common set of variables of the same type for all countries. This seems to be a particularly effective strategy to make international comparisons more reliable. However, like in the case of sub-samples selection, differences in the specific content of LIS variables with the same names may reduce the actual cross-country comparability of variables and results. The process of constructing dummy variables for human capital and socio-demographic characteristics results in diversified sets of controls which are not equally accurate and which cannot always be directly compared. The attempt to define a uniform set of controls for all countries, hence, is bound to be only partially successful. The treatment of the original LIS variables used for the construction of regression controls is presented in full detail in Appendix 5.A. The control variables included in the wage equation for each country are summarized in the following lists. Some general comments on the choice of these variables are proposed afterwards.

a) United States

age and its square; 6 dummy variables for education - completed junior high school, some high school, completed high school, some college/university, completed college/university bachelor, post-graduate studies (the base group, i.e. the omitted dummy variable in the regression which also includes an intercept term, refers to individuals with some or completed elementary school education (96 cases)); 4 dummy variables for marital status - married, widowed, divorced, separated (the reference group consists of never married individuals (968 cases)); 6 dummy variables for skill level - machine operating blue-collar worker, precision blue-collar worker, white-collar worker, technician, professional, manager (the excluded dummy variable represents manual workers (1,289 cases)).

b) Canada

age and its square; 6 dummy variables for education - some secondary school, completed secondary (short) or vocational school, completed university-oriented high school, some college diploma, completed college diploma, university degree (the base group refers to individuals with elementary school education (678 cases)); 2 dummy variables for marital status - married, other marital status (the reference group consists of never married individuals (1,025 cases)); 4 dummy variables for skill level - machine operating blue-collar worker,
white-collar worker, professional, manager (the excluded dummy variable represents manual workers (1,218 cases)).

c) Australia
age and its square: 4 dummy variables for education - completed secondary school, trade certificate, other certificate, bachelor degree or higher (the base group refers to individuals with primary school or some secondary school education (1,272 cases)); 2 dummy variables for marital status - married, separated/widowed/divorced (the reference group consists of never married individuals (930 cases)); 4 dummy variables for skill level - machine operating blue-collar worker, white-collar worker, professional, manager (the excluded dummy variable represents labourers/manual workers (521 cases)).

d) Germany
age and its square; 4 dummy variables for education - vocational school, technical high school, general high school, other education (the base group refers to individuals with elementary school education (1,573 cases)); 4 dummy variables for marital status - married, separated, widowed, divorced (the reference group consists of never married individuals (412 cases)); 9 dummy variables for skill level - semi-skilled worker, skilled worker/craftsman, foreman, building foreman, white-collar foreman, white-collar worker, qualified white-collar worker, high-qualified white-collar worker, white-collar manager (the excluded dummy variable represents unskilled workers (171 cases)).

e) Netherlands
age and its square; 3 dummy variables for education - extended primary school, secondary school, university (the base group refers to individuals with primary school education (621 cases)); 3 dummy variables for marital status - married, widowed, divorced/separated (the reference group consists of unmarried individuals (443 cases)); 2 dummy variables for skill level - intermediate level, higher level (the excluded dummy variable represents workers with none/lower skill level (1,167 cases)).

51 For Australia, differently from the other countries, age is not represented by a continuous variable, but by the mid-points of age classes of width equal to 4 years for the age interval 17-24 and subsequently of width equal to 5 years for the age interval 25-79, plus the initial values of the entire age interval, 15 and 16 years.
The age variable is used as a proxy for labour market experience, a factor which is of great importance, according to human capital theory, in explaining the shape of earnings profiles over time. In the human capital literature, experience is usually calculated as age minus years of schooling minus five/six (the age at which school begins). An analogous measure of experience cannot be computed with the LIS data, because in the data-sets considered for the present study the education variable is defined in terms of years of schooling only in one case (the United States), while for the other countries it refers to educational qualifications. Besides, previous experimentation with the German SOEP data used in Chapter 4 - where I can construct a direct measure of working experience using biographical schemes - shows that age and experience are very strongly correlated across individuals and that age is much more easily surveyed without measurement errors. The variables for education are specified as sets of dummies representing different educational qualifications. On the one hand, this just reflects the original nature of the majority of the LIS education variables. In the case of the United States and partly of Canada, years of schooling are transformed into the corresponding qualifications (courses of studies only started or actually completed). On the other hand and more relevantly, this specification conforms to the considerations suggested in Chapter 2 and already applied in Chapter 4. A continuous variable measuring the years of full-time schooling does not necessarily represent the most appropriate choice to capture the effect of education on earnings (Psacharopoulos and Layard, 1979). Dummy variables for marital status are introduced to describe an observable exogenous characteristic that may affect individuals' decisions of investment in human capital and its marginal returns. Finally, the dummy variables for skill levels are supposed to incorporate other forms of human capital investment, like the type and amount of explicit and implicit on-the-job training received for a specific occupation. For the United States, Canada, and Australia, the dummies are based on the workers' actual occupations. In the case of Germany, they are derived from a direct measure of individuals' skill level. For the Netherlands, they are defined in terms of general occupational training received by each worker.

Given the limited number of LIS variables available at the person level, I have not the possibility to construct other explanatory variables that would be proper to include in the specification of a wage equation like the one considered here. In particular, I have no information about working conditions capable to quantify the relevance of compensating wage differentials. Other socio-demographic aspects such as nationality and race would be useful.
in modelling wage determinants for countries characterized by considerable immigration phenomena, as it is the case with all the countries examined in the present study. A measure for workers' tenure in their current job could be appropriate to evaluate the effect on wages of investments in firm-specific human capital. Firm-level variables like the employer's size and the degree of unionization within the firm might be suitable to capture efficiency wage and insider-outsider forces in wage determination. These types of controls are usually taken into account in the more detailed studies utilized in Chapter 4 for cross-country comparisons.

A final aspect of cross-country comparability of variables and results concerns the definition of the last group of variables entering the wage regression specification, the dummy variables for industry affiliation. The various studies used in Chapter 4 employ different sets of industry dummies, which reflect the different national systems of classification of production activities. Results in terms of inter-industry wage differentials are, therefore, not immediately comparable across countries and it is necessary to aggregate the originally estimated differentials into a common, less detailed classification by employment-weighted averages. This procedure may introduce a considerable amount of imprecision in the measurement of industry differentials.

With the LIS data-sets I have the possibility to define a priori a common set of industries for all countries, performing the necessary aggregations directly through the LIS industry affiliation variable. Differences among countries in the content of this variable lead to a final definition of only 9 sectors (agriculture, mining, manufacturing, public utilities and other community services, construction, trade, transport and communications, finance, insurance and real estate, and personal and social services), with countries characterized by a very detailed initial classification - like the United States and Germany - experiencing a drastic loss of information. Again, direct comparability of results can be achieved only at the cost of a considerable reduction in accuracy. The final set of 9 industries nearly corresponds to the 1-digit classification used in other studies of the inter-industry wage structure (Krueger and Summers, 1988; Borland and Suen, 1990). The details of the process of aggregation that leads to the definition of industry dummies are given, for each country, in Appendix 5.A.

In order to evaluate the homogeneity of these aggregations across countries, I compare the frequency distributions of employment by sector within the LIS sub-samples used in my regression analysis. And to assess their overall correctness, I also compare the LIS sample distributions with population distributions derived from OECD data for 1985 (OECD, 1987).
Table 5.1 reports, in absolute and relative terms, the distributions by sector of sample and population employment for the five countries considered. Sample and population distributions of sector employment as a percentage of total employment are then graphed in Figure 5.1 and 5.2 respectively. As we can see in Figure 5.1, sample distributions by sector are sufficiently similar across countries. All countries, for example, present very small percentages of employment in the agriculture and mining sectors and the highest relative frequency in the manufacturing sector. Comparing Figure 5.1 with Figure 5.2, we also notice that sample distributions adequately represent the underlying population distributions and that some differences among countries in the distribution of sample employment simply reflect analogous differences in the distribution of population employment. There is however a certain number of anomalies, justified by the inevitably approximate aggregation criteria adopted in the definition of the 9 industry sectors and by the specific nature of the selected sub-samples, that are worth taking into proper account in evaluating the results of my later regression analysis. The sample proportion of workers employed in the agriculture sector is smaller than the population proportion for all countries. This is likely to be due to the exclusion of self-employment from the sub-samples, whereas the populations do include it. The same remark can be made with respect to the construction sector. In the mining sector, Canada presents a sample percentage of employment that is much larger than the percentages of the other countries and more than the double of its population percentage. A possible explanation is in the original LIS definition of this industry, which in the case of Canada includes other primary activities that are classified elsewhere for the other countries. The proportion of German workers in the manufacturing sector is considerably larger than in other countries. This partly reflects a characteristic of the German economy, as it is shown by the fact that population data present the same phenomenon. But it certainly reflects also the exclusion from the sub-sample of a vast category of civil servants, the Beamten, which reduces the relative weight of sectors like transport and communications and especially like personal and social services (this last sector presents a population percentage which is almost the double of the sample percentage), and increases the proportion of manufacturing employment. These considerations apply, but to a minor extent, also to the case of the United States. Frequencies in the public utilities and community services sector must be considered together with frequencies in the personal and social services sector. Canada and Australia exhibit comparatively high values for the first sector and comparatively low values for the
TABLE 5.1
Distribution of male employment by sector in the LIS samples and in the populations*: employment per sector and percentage of total employment per sector

<table>
<thead>
<tr>
<th>Sectors</th>
<th>United States</th>
<th>Canada</th>
<th>Australia</th>
<th>Germany</th>
<th>Netherlands</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Agriculture</td>
<td>85</td>
<td>2,662</td>
<td>90</td>
<td>441</td>
<td>89</td>
</tr>
<tr>
<td>2. Mining</td>
<td>55</td>
<td>812</td>
<td>302</td>
<td>169</td>
<td>84</td>
</tr>
<tr>
<td>3. Manufacturing</td>
<td>1,218</td>
<td>14,094</td>
<td>1,067</td>
<td>1,438</td>
<td>790</td>
</tr>
<tr>
<td>4. Public utilities, community services</td>
<td>127</td>
<td>1,039</td>
<td>598</td>
<td>698</td>
<td>680</td>
</tr>
<tr>
<td>5. Construction</td>
<td>295</td>
<td>6,340</td>
<td>289</td>
<td>527</td>
<td>214</td>
</tr>
<tr>
<td>6. Trade</td>
<td>1,079</td>
<td>12,271</td>
<td>944</td>
<td>1,395</td>
<td>554</td>
</tr>
<tr>
<td>7. Transport, communications</td>
<td>333</td>
<td>4,348</td>
<td>618</td>
<td>580</td>
<td>426</td>
</tr>
<tr>
<td>8. Finance, insurance, real estate</td>
<td>407</td>
<td>4,848</td>
<td>387</td>
<td>535</td>
<td>286</td>
</tr>
<tr>
<td>9. Personal, social services</td>
<td>801</td>
<td>13,478</td>
<td>705</td>
<td>728</td>
<td>402</td>
</tr>
</tbody>
</table>

Percentage of total employment per sector

<table>
<thead>
<tr>
<th>Sectors</th>
<th>Percentage of total employment per sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Agriculture</td>
<td>1.93</td>
</tr>
<tr>
<td>2. Mining</td>
<td>1.25</td>
</tr>
<tr>
<td>3. Manufacturing</td>
<td>27.68</td>
</tr>
<tr>
<td>4. Public utilities, community services</td>
<td>2.89</td>
</tr>
<tr>
<td>5. Construction</td>
<td>6.70</td>
</tr>
<tr>
<td>6. Trade</td>
<td>24.52</td>
</tr>
<tr>
<td>7. Transport, communications</td>
<td>7.57</td>
</tr>
<tr>
<td>8. Finance, insurance, real estate</td>
<td>9.25</td>
</tr>
<tr>
<td>9. Personal, social services</td>
<td>18.20</td>
</tr>
</tbody>
</table>

* Source: my calculations based on OECD (1987).
FIGURE 5.1
Employment distribution by sector: *samples* (LIS), male workers

FIGURE 5.2
Employment distribution by sector: *populations* (OECD), male workers
second. The reverse is true for the Netherlands. This is due to the different criteria used to classify certain services: in Canada and Australia, community services are relatively important and are entirely classified together with public utilities in a single sector; in other countries, and especially in the Netherlands, a part of community services is classified in a non-separable way together with personal and social services. This problem with the original codification of activities is reflected also in the population frequencies. Percentages of sample employment in the trade sector are also affected by minor differences in the original classifications of certain services (like repair, catering, and accommodation services), which in some countries are included in the trade sector, while in others are considered as part of the personal services sector.

As it can be deduced from all these observations, comparability of LIS data and results is far from being perfect. The specification of industry dummies proposed here seems however the most accurate attainable, if I want to define a common set of industries for all countries. The vector of industry variables entering the wage regressions consists, therefore, of the same 8 sector dummies for all the countries considered. They indicate workers' affiliation to the mining, manufacturing, public utilities and community services, construction, trade, transport and communications, finance, insurance and real estate, and personal and social services sectors. The omitted industry dummy - the base group of workers - refers to the agriculture sector.

Two other variables are used in the estimated wage equations for all countries, in order to deal with the problem of missing values. Instead of excluding from the sub-samples observations with missing values in any of the explanatory variables, which would reduce further on the sample sizes, I prefer to introduce a separate dummy variable for missing data about education and industry affiliation. This last variable is later maintained only for Germany and the Netherlands, because in the other countries none of the individuals reports missing affiliation.

Two different specifications of the wage regression model are estimated: the first is the general model, which includes both control variables for human capital and socio-demographic characteristics and industry dummies; the second is a restricted model, which involves only industry dummy variables. The detailed results for the estimated wage equations, both with and without controls, are presented in Appendix 5.C.
5.3 Empirical Evidence: Main Results

Table 5.2 and Table 5.3 present, for the five countries considered, the results of cross-section estimates of inter-sectoral wage differentials in a wage equation without and with controls for human capital and socio-demographic characteristics respectively. Following the approach already adopted in Chapter 4, wage differentials are reported as deviations from the employment-weighted mean differential. This mean differential is obtained calculating the employment-weighted average of wage differentials for all sectors as they emerge from the wage regression - that is, relative to the excluded sector, agriculture - and treating the omitted sector variable as having a zero effect on wages. The employment shares by sector used as weights to compute the weighted average are those resulting from each sub-sample involved. Table 5.2 and Table 5.3 report the differences between each estimated coefficient of the industry dummy variables and the employment-weighted mean differential. The resulting statistics, therefore, represent the proportionate differences in wages between the employees in a given sector and the average employee in the whole economy. Moreover, this transformation in deviation form makes the wage differentials independent of the arbitrarily chosen base sector, as proved in the general Appendix to the thesis.

The standard errors appearing both in Table 5.2 and in Table 5.3 refer to differentials in deviation form - that is, to the differentials that are actually contained in the various columns of the two Tables - and are directly comparable with them in order to evaluate the statistical significance of each differential. They can be derived from the OLS standard errors of the estimated coefficients for the industry dummy variables included in the wage equations, since each differential in deviation form is a linear combination of all the estimated industry dummy coefficients. The calculations needed for this derivation are illustrated in full detail in the general Appendix to the thesis. A major advantage of the transformation of the standard errors is that it gives the possibility to take into account, in cross-country comparisons, the wage differential of the base sector (agriculture in my case), because it also provides an

\[ \delta_k = \text{industry dummy coefficient estimated in the wage regression for industry } k \text{ affiliation, the corresponding differential in deviation form is defined as } (\delta_k - \bar{\delta}), \text{ where } \bar{\delta} \text{ is in turn the employment-weighted average of all the estimated industry dummy coefficients } \delta_k, k = 1, \ldots, K. \text{ From the OLS estimation of the wage equation, I obtain the estimated standard error } \hat{\delta}_k \text{ of each industry dummy coefficient and from these standard errors I can, therefore, derive the standard error of the differential in deviation form.} \]
TABLE 5.2
Estimated wage differentials without controls for human capital:
deviations from the employment-weighted mean differential
(standard errors of the differentials in deviation form* in parentheses)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Agriculture</td>
<td>-0.650**</td>
<td>-0.801**</td>
<td>-0.483**</td>
<td>-0.218</td>
<td>-0.217*</td>
</tr>
<tr>
<td></td>
<td>(0.065)</td>
<td>(0.059)</td>
<td>(0.041)</td>
<td>(0.115)</td>
<td>(0.084)</td>
</tr>
<tr>
<td>2. Mining</td>
<td>0.380**</td>
<td>0.258**</td>
<td>0.293**</td>
<td>0.063</td>
<td>0.236</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.031)</td>
<td>(0.043)</td>
<td>(0.099)</td>
<td>(0.199)</td>
</tr>
<tr>
<td>3. Manufacturing</td>
<td>0.116**</td>
<td>0.052**</td>
<td>-0.039**</td>
<td>0.025*</td>
<td>-0.028</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.012)</td>
<td>(0.010)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>4. Public utilities, community services</td>
<td>0.279**</td>
<td>0.058**</td>
<td>0.106**</td>
<td>0.088</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.022)</td>
<td>(0.014)</td>
<td>(0.083)</td>
<td>(0.115)</td>
</tr>
<tr>
<td>5. Construction</td>
<td>-0.036</td>
<td>-0.053</td>
<td>-0.064*</td>
<td>-0.070*</td>
<td>-0.126**</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.032)</td>
<td>(0.026)</td>
<td>(0.035)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>6. Trade</td>
<td>-0.227**</td>
<td>-0.180**</td>
<td>-0.160**</td>
<td>-0.200**</td>
<td>-0.082**</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.017)</td>
<td>(0.015)</td>
<td>(0.031)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>7. Transport, communications</td>
<td>0.134**</td>
<td>0.096**</td>
<td>0.082**</td>
<td>-0.013</td>
<td>-0.094**</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.021)</td>
<td>(0.018)</td>
<td>(0.050)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>8. Finance, insurance, real estate</td>
<td>0.100**</td>
<td>0.029</td>
<td>0.037</td>
<td>0.310**</td>
<td>0.109**</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.028)</td>
<td>(0.022)</td>
<td>(0.055)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>9. Personal, social services</td>
<td>0.035</td>
<td>0.027</td>
<td>0.081**</td>
<td>0.030</td>
<td>0.084**</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.020)</td>
<td>(0.018)</td>
<td>(0.031)</td>
<td>(0.014)</td>
</tr>
</tbody>
</table>

Measures of variability of wage differentials:

Adjusted SD à la Krueger and Summers*a
0.156  0.097  0.118  0.044  0.000d

Adjusted SD of differentials in deviation form*
0.283  0.283  0.202  0.135  0.099

(continued)
TABLE 5.2 (continued)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{R}^2$</td>
<td>0.078</td>
<td>0.069</td>
<td>0.093</td>
<td>0.028</td>
<td>0.036</td>
</tr>
<tr>
<td>$F$-statistic for no industry effect</td>
<td>47.292**</td>
<td>47.482**</td>
<td>46.385**</td>
<td>8.861**</td>
<td>9.731**</td>
</tr>
<tr>
<td>Sample size</td>
<td>4,400</td>
<td>5,000</td>
<td>3,543</td>
<td>2,447</td>
<td>2,084</td>
</tr>
</tbody>
</table>

* The standard errors for the wage differentials in deviation form are derived from the OLS standard errors of the industry dummy coefficients in the estimated wage equation. The calculations needed for such derivation are illustrated in the general Appendix to the thesis.

` Estimate of the adjusted standard deviation obtained using equation (5.1) in Section 5.3.

' Estimate of the adjusted standard deviation obtained using equation (5.2) in Section 5.3.

d Not computable, since the variance of the estimated coefficients is less than the average squared standard error (see equation (5.1) in Section 5.3).

* Statistically different from 0 at the 5% significance level.

** Statistically different from 0 at the 1% significance level. The $F$ test that industry dummy coefficients jointly equal 0 rejects at the 1% level.
TABLE 5.3
Estimated wage differentials with controls for human capital:
deviations from the employment-weighted mean differential
(standard errors of the differentials in deviation form in parentheses)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Agriculture</td>
<td>-0.358**</td>
<td>-0.578**</td>
<td>-0.371**</td>
<td>-0.069</td>
<td>-0.093</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.054)</td>
<td>(0.036)</td>
<td>(0.102)</td>
<td>(0.067)</td>
</tr>
<tr>
<td>2. Mining</td>
<td>0.309**</td>
<td>0.233**</td>
<td>0.285**</td>
<td>0.116</td>
<td>0.200</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.028)</td>
<td>(0.036)</td>
<td>(0.089)</td>
<td>(0.159)</td>
</tr>
<tr>
<td>3. Manufacturing</td>
<td>0.117**</td>
<td>0.098**</td>
<td>0.008</td>
<td>0.043**</td>
<td>0.035*</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.015)</td>
<td>(0.011)</td>
<td>(0.009)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>4. Public utilities, community services</td>
<td>0.252**</td>
<td>-0.112**</td>
<td>-0.004</td>
<td>0.055</td>
<td>-0.082</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.022)</td>
<td>(0.013)</td>
<td>(0.074)</td>
<td>(0.092)</td>
</tr>
<tr>
<td>5. Construction</td>
<td>0.070*</td>
<td>-0.011</td>
<td>0.002</td>
<td>-0.066*</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.030)</td>
<td>(0.022)</td>
<td>(0.032)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>6. Trade</td>
<td>-0.118**</td>
<td>-0.084**</td>
<td>-0.080**</td>
<td>-0.133**</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.016)</td>
<td>(0.013)</td>
<td>(0.029)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>7. Transport, communications</td>
<td>0.119**</td>
<td>0.079**</td>
<td>0.084**</td>
<td>0.003</td>
<td>-0.023</td>
</tr>
<tr>
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<td>(0.027)</td>
<td>(0.019)</td>
<td>(0.015)</td>
<td>(0.045)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>8. Finance, insurance, real estate</td>
<td>0.006</td>
<td>-0.042</td>
<td>0.005</td>
<td>0.096</td>
<td>0.044*</td>
</tr>
<tr>
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<td>(0.024)</td>
<td>(0.025)</td>
<td>(0.019)</td>
<td>(0.051)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>9. Personal, social services</td>
<td>-0.119**</td>
<td>-0.009</td>
<td>0.029</td>
<td>-0.074*</td>
<td>-0.039**</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.015)</td>
<td>(0.029)</td>
<td>(0.012)</td>
</tr>
</tbody>
</table>

Measures of variability of wage differentials:

Adjusted SD à la Krueger and Summers

<table>
<thead>
<tr>
<th></th>
<th>Adjusted SD à la Krueger and Summers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.130</td>
</tr>
</tbody>
</table>

Adjusted SD of differentials in deviation form

<table>
<thead>
<tr>
<th></th>
<th>Adjusted SD of differentials in deviation form</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.191</td>
</tr>
</tbody>
</table>

(continued)
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{R}^2$</td>
<td>0.347</td>
<td>0.261</td>
<td>0.356</td>
<td>0.230</td>
<td>0.389</td>
</tr>
<tr>
<td>$F$-statistic for no industry effect</td>
<td>31.195''</td>
<td>33.927''</td>
<td>28.052''</td>
<td>5.094''</td>
<td>2.866''</td>
</tr>
<tr>
<td>Sample size</td>
<td>4,400</td>
<td>5,000</td>
<td>3,543</td>
<td>2,447</td>
<td>2,084</td>
</tr>
</tbody>
</table>

* Controls for human capital include: age, age squared, dummies for education, marital status, and skill level.

* See note 4 of Table 5.2.

* See note 5 of Table 5.2.

* See note 6 of Table 5.2.

* Not computable, since the variance of the estimated coefficients is less than the average squared standard error (see equation (5.1) in Section 5.3).

* Statistically different from 0 at the 5% significance level.

** Statistically different from 0 at the 1% significance level. The $F$ test that industry dummies coefficients jointly equal 0 rejects at the 1% level.
estimate of its standard error. In other, previously cited studies of the inter-industry wage structure (Krueger and Summers, 1988; Borland and Suen, 1990; Edin and Zetterberg, 1992), the authors consider only the OLS standard errors obtained from the estimated wage equation and rely on them to assess the significance of individual differentials in deviation form. As a result, they ignore the differential of the base sector - which is different in the various studies - with potentially serious consequences for the accuracy of cross-country comparisons. What is more, the procedure adopted by these authors does not seem theoretically justified, as thoroughly explained in the general Appendix. In practice, however, the difference between OLS standard errors and standard errors of differentials in deviation form may be negligible. As illustrated in Section A.4 of the general Appendix, this occurs when at least one of two conditions is satisfied. The first is when the variance-covariance matrix of the estimated OLS coefficients is characterized by small variances on the diagonal and by covariance terms very close to zero. Such a variance-covariance matrix is obtained if the specification chosen for the regression model is sufficiently close to the true data generating process. The second condition is that employment shares by industry must be very small for all industries. This happens when the type of classification chosen for the construction of industry dummy variables is disaggregate enough to guarantee a large number of sectors and a uniform distribution of employees across sectors. In any case, these are conditions that need to be verified for the specific model considered. A control on these aspects of the estimated results is made in the analysis of the German inter-industry wage structure of Chapter 4, where the difference between OLS standard errors and standard errors of differentials in deviation form is only of order $10^3$. It seems hence justified, in that context, to use OLS standard errors for inference procedures. In the case of the wage equations estimated with LIS data, however, both conditions are no longer satisfied, because of the limited number of human capital control variables that can be included in the specification of the regression model and because of the rather aggregate industry classification adopted (9 sectors only). The use of OLS standard errors, therefore, gives rise to differences in the evaluation of the statistical significance of individual differentials in deviation form which are of considerable size.

\[ \text{If the base sector is treated as having a zero effect on wages in a wage regression which includes an intercept term, its differential in deviation form is defined as } (0 - \delta) = -\delta \text{ The standard error of this differential can, therefore, be derived from OLS standard errors.} \]
To summarize the overall variability in inter-industry wages, I present two alternative measures of the standard deviation of estimated differentials. The first is the adjusted standard deviation obtained applying the formula suggested by Krueger and Summers (1988, p.267):

\[
SD(\delta) = \sqrt{\text{var}(\delta) - \frac{1}{K-1} \sum_{k=1}^{K-1} \delta_{COEk}^2}
\]

(5.1)

where \(\delta_{COEk}\) is the standard error of the estimated coefficient \(\hat{\delta}_k\) for each dummy of sector \(k = 1, ..., K-1\), ignoring industry \(K\), agriculture (see Chapter 4). The adjustment is necessary because each coefficient \(\hat{\delta}_k\) is an estimate of the true parameter \(\delta_k\), which entails a least squares sampling error. As a consequence, the standard deviation of \(\delta\) would be an upwardly biased estimate of the standard deviation of \(\delta\). The second is the adjusted standard deviation obtained applying the following formula:

\[
SD(\delta) = \sqrt{\text{var}(\delta - \bar{\delta}) - \frac{1}{K} \sum_{k=1}^{K} \delta_{DEVk}^2}
\]

(5.2)

where \((\delta_k - \bar{\delta})\) is the estimated differential in form of deviation from the employment-weighted mean differential \(\bar{\delta}\) for each sector \(k = 1, ..., K\), and \(\delta_{DEVk}\) is the related standard error, obtained from the transformation described earlier. The \(K\) sectors include here also agriculture, the base sector excluded from the set of industry dummies in the wage equation and for which hence \((\hat{\delta}_1 - \bar{\delta}) = -\bar{\delta}\). This formula seems preferable to the one proposed by Krueger and Summers for at least two reasons: (i) it provides a summary measure of the variability of wage differentials in deviation form - as they appear in the Tables - with reference to both the estimate of the standard deviation and the adjustment factor; (ii) it takes into account the differential of the base sector - agriculture - which is
otherwise ignored, since its coefficient and its standard error are not defined in the OLS estimate of the wage equation.

The five columns of Table 5.2 present the raw inter-sectoral wage differentials estimated in a wage equation without controls for human capital and socio-demographic characteristics for the various countries. Considerable cross-country differences emerge clearly. The main findings in terms of range, average size, individual statistical significance, and dispersion of raw differentials are summarized by the following table:

<table>
<thead>
<tr>
<th>Minimum differential</th>
<th>Maximum differential</th>
<th>Average differential in absolute size</th>
<th>Statistically significant differentials: 5%</th>
<th>Adjusted SD of differentials</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States 1986</td>
<td>-65%</td>
<td>0.217</td>
<td>7</td>
<td>28.3%</td>
</tr>
<tr>
<td>1987</td>
<td>-80%</td>
<td>0.173</td>
<td>6</td>
<td>28.3%</td>
</tr>
<tr>
<td>Australia 1986</td>
<td>-48%</td>
<td>0.149</td>
<td>8</td>
<td>20.2%</td>
</tr>
<tr>
<td>1987</td>
<td>-22%</td>
<td>0.113</td>
<td>4</td>
<td>13.5%</td>
</tr>
<tr>
<td>Germany 1985</td>
<td>-22%</td>
<td>0.109</td>
<td>6</td>
<td>9.9%</td>
</tr>
<tr>
<td>1987</td>
<td>+38%</td>
<td>0.217</td>
<td>7</td>
<td>28.3%</td>
</tr>
<tr>
<td>Netherlands 1987</td>
<td>+26%</td>
<td>0.173</td>
<td>6</td>
<td>28.3%</td>
</tr>
<tr>
<td></td>
<td>+29%</td>
<td>0.149</td>
<td>8</td>
<td>20.2%</td>
</tr>
<tr>
<td></td>
<td>+31%</td>
<td>0.113</td>
<td>4</td>
<td>13.5%</td>
</tr>
<tr>
<td></td>
<td>+24%</td>
<td>0.109</td>
<td>6</td>
<td>9.9%</td>
</tr>
</tbody>
</table>

To stress the importance of using standard errors of differentials in deviation form, rather than unadjusted OLS standard errors, it is worth noting that the evaluation of individual significance of differentials would be quite different if the latter were considered. In the case of the United States, only 3 differentials would be significantly different from zero at the 1% level. For Canada and Australia, only 2 differentials would remain significant at the 1% level. In the case of Germany and the Netherlands, none of the differentials would be statistically different from zero at the same significance level. As previously explained, these results depend on the values of the variances and covariances of the estimated OLS industry dummy coefficients and, especially, of employment shares by industry, all sufficiently greater than zero to generate considerable differences between standard errors of differentials in deviation form and unadjusted OLS standard errors. Given the relative magnitudes of variances, covariances and employment shares in this particular model and the way they combine in the derivation of standard errors of differentials in deviation form, these are all smaller than unadjusted OLS standard errors.

54 Unadjusted OLS standard errors for industry coefficients estimated without controls can be found in Tables 5.C1-5.C5 of Appendix 5.C.

55 See Section A.4 in the general Appendix to the thesis for a more detailed discussion about this issue.

248
Although for all countries the inter-sectoral differentials are jointly statistically significant (the appropriate $F$-statistics, in all five countries, enable rejection of the null hypothesis at the 1% significance level), the size, individual significance, and overall variability of differentials suggest the existence of a ranking among the various countries: on the one hand, the United States and Canada exhibit a similar situation, characterized by differentials of very high value, highly significant in the majority of cases, and considerably variable across sectors; on the other hand, Germany and the Netherlands present differentials of lower value, less strongly significant, and, above all, remarkably less variable across sectors: Australia represents a sort of intermediate case between these two extremes.

This global evaluation seems to be confirmed and reinforced if we consider the results for cross-section estimates of inter-sectoral wage differentials in wage equations with controls for human capital and socio-demographic characteristics. Table 5.3 reports these results for the five countries examined. The main findings can be summarized as follows:

<table>
<thead>
<tr>
<th></th>
<th>United States</th>
<th>Canada</th>
<th>Australia</th>
<th>Germany</th>
<th>Netherlands</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum differential</td>
<td>-36%</td>
<td>-58%</td>
<td>-37%</td>
<td>-13%</td>
<td>-9%</td>
</tr>
<tr>
<td>Maximum differential</td>
<td>+31%</td>
<td>+23%</td>
<td>+28%</td>
<td>+12%</td>
<td>+20%</td>
</tr>
<tr>
<td>Average differential</td>
<td>0.163</td>
<td>0.138</td>
<td>0.096</td>
<td>0.073</td>
<td>0.061</td>
</tr>
</tbody>
</table>

Statistically significant differentials:

- 5%
  - United States: 8
  - Canada: 6
  - Australia: 4
  - Germany: 4
  - Netherlands: 3

- 1%
  - United States: 7
  - Canada: 6
  - Australia: 4
  - Germany: 2
  - Netherlands: 1

Adjusted SD of differentials:

- United States: 19.1%
- Canada: 21.1%
- Australia: 16.0%
- Germany: 5.6%
- Netherlands: 4.7%

Again, the use of simple OLS standard errors, instead of standard errors transformed in deviation form, would imply different results for the tests of statistical significance of individual differentials. In the case of the United States, only 2 differentials would be significantly different from zero at the 1% level. For Canada and Australia, only 1 differential would remain significant at the 1% level. In the case of Germany and the Netherlands, none of the differentials would be statistically different from zero at the same significance level. As in the case of differentials estimated without controls, the relative magnitudes of variances and covariances of OLS coefficients and of employment shares in this particular model

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56 Unadjusted OLS standard errors for industry coefficients estimated with controls can be found in Tables 5.C6-5.C10 of Appendix 5.C.
produce standard errors of differentials in deviation form which are all considerably smaller than unadjusted OLS standard errors.

These results for industry differentials corrected for human capital and socio-demographic differences seem to confirm the existence of a ranking among countries: the United States and Canada continue to present differentials of considerable size, strongly significant in the majority of cases, and with a substantial variability across sectors. Germany and the Netherlands present much smaller differentials, statistically significant only in a few cases, and with a quite moderate variability across sectors (according to the measure suggested by Krueger and Summers, such variability is even zero). Australia still ranges as an intermediate case.

Wage differentials appearing in Table 5.2 and in Table 5.3 are plotted in Figure 5.3 and in Figure 5.4 respectively. The Figures help to illustrate some of the characteristics of the inter-sectoral wage structures in the various countries. The introduction of human capital and socio-demographic controls in the wage regressions narrows the global range of variation of differentials, but, at the same time, it reduces the degree of similarity among countries. Although the effect of control variables is generally that of reducing the size and dispersion of industry wage differentials in all countries, the impact of these controls is, in fact, rather different in the various countries. The main changes in the structures of differentials due to the introduction of control variables are summarized in the following table:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in the width of the interval between minimum and maximum differential</td>
<td>-35%</td>
<td>-23%</td>
<td>-15%</td>
<td>-53%</td>
<td>-35%</td>
</tr>
<tr>
<td>Change in the average differential in absolute size</td>
<td>-25%</td>
<td>-20%</td>
<td>-35%</td>
<td>-36%</td>
<td>-44%</td>
</tr>
<tr>
<td>Change in the statistical significance of individual differentials</td>
<td>improved</td>
<td>unchanged</td>
<td>worsened</td>
<td>mixed</td>
<td>worsened</td>
</tr>
<tr>
<td>Change in the adjusted SD of differentials</td>
<td>-33%</td>
<td>-25%</td>
<td>-21%</td>
<td>-59%</td>
<td>-53%</td>
</tr>
<tr>
<td>Pearson correlation between differentials estimated without and with controls</td>
<td>0.932  (0.000)</td>
<td>0.954  (0.000)</td>
<td>0.960  (0.000)</td>
<td>0.792  (0.005)</td>
<td>0.712  (0.016)</td>
</tr>
<tr>
<td>Spearman correlation between differentials estimated without and with controls</td>
<td>0.917  (0.001)</td>
<td>0.667  (0.05)</td>
<td>0.733  (0.025)</td>
<td>0.750  (0.025)</td>
<td>0.550  (0.10)</td>
</tr>
</tbody>
</table>

* Based on Kendall and Stuart (1977, p.416, §16.28) r-transformation.

b Based on Zar's distribution table (Zar, 1972, p.579).
FIGURE 5.3
Estimated wage differentials \textit{without} controls for human capital

FIGURE 5.4
Estimated wage differentials \textit{with} controls for human capital
These statistics seem to indicate that the inclusion of controls for human capital and socio-demographic differences changes the estimated inter-industry differentials only to a limited extent in the United States and Canada, while it has a substantial impact on the wage structures of Germany and the Netherlands. The case of Australia represents a somehow mixed picture.

Differences in the impact of controls for human capital, socio-demographic characteristics and working conditions on the structure of estimated wage differentials of the various countries can also be shown in another, more indirect way. Appendix 5.D presents the details of a comparison between the inter-industry differentials estimated with LIS data and those estimated by other authors with different data sources for a selection of countries: the United States, Australia, and Germany. The studies providing this alternative evidence (Krueger and Summers, 1988; Borland and Suen, 1990; Chapter 4 of this thesis) are those already employed in Chapter 4. The limited amount of variables available in the LIS data-sets make the analysis in the present Chapter less accurate than the ones proposed in these other studies. Therefore, I can evaluate the effect of a larger, more detailed set of controls on the inter-industry wage structures of these three countries. The results in Appendix 5.D seem to confirm the previous conclusion. A richer set of controls has only a minor impact in the United States, a mixed effect in Australia, and a considerable impact in Germany. The Pearson and Spearman correlations between differentials estimated with a small amount of controls and differentials estimated with a large amount of controls (i.e. between LIS and other studies differentials) are comparable - in size and significance - with the correlations between differentials estimated without and with controls from LIS data exclusively, presented in the above summary table.

Dissimilarities in the proportionate relevance of human capital and socio-demographic factors with respect to industry affiliation suggest that the relative intensity of competitive and non-competitive forces in wage determination may vary across countries. This result seems to confirm that institutional aspects of the various national labour markets play an important role in accounting for the cross-country pattern of wage structures. The ranking among countries emerging from my empirical analysis is in fact consistent with that delineated in terms of degree of centralization of wage bargaining procedures, as previously discussed in Chapter 2.
5.4 Cross-Country Comparisons of Inter-Industry Wage Structures: Correlation Coefficients and Minimum Distance Chi-Square Tests

5.4.1 Pearson and Spearman Correlation Coefficients

To evaluate in greater detail the degree of similarity of inter-industry wage structures across countries, a first approach, already utilized in the preceding Chapters, consists in the calculation of correlation coefficients between vectors of estimated differentials. Like other authors, referred to in Chapter 4, I use vectors of differentials in deviation form, $D_i = \delta_i - \bar{\delta}$; but unlike them, I also consider for all countries the base sector of my wage regression models (agriculture). This certainly increases the accuracy of cross-country comparisons and should be taken into account when comparing my findings with those provided in other studies of the international wage structure. The results of the correlation analysis are reported in Table 5.4, in terms of Pearson and Spearman correlation coefficients. The motivation to consider both measures of correlation has been already given in Chapter 3. The Pearson product-moment correlation is more sensitive to the data and represents a measure of similarity between countries in a strong sense, because it relies on the exact size of differentials. The Spearman correlation, instead, considers only the rank-order of differentials across industries and refers to a weaker concept of similarity that, however, may be of interest in the present framework. It measures, in fact, if the sectors paying wages above/below the average wage tend to be the same in the various countries. Since differentials are expressed in deviation form, both correlations are independent of the sector chosen as a base in the regression model. Correlations are computed for inter-industry differentials estimated without and with control variables in the wage equation.

The results in Table 5.4 for the differentials estimated without controls indicate, both through the Pearson and the Spearman correlations, a relatively high degree of similarity between the United States, Canada, and Australia, with correlations significantly greater than zero at the 0.5% level, but a clear dissimilarity between these three countries and Germany and the Netherlands. The Pearson correlation also shows a certain similarity between Australia and the Netherlands, being significantly greater than zero at the 0.5% level, but this result is not supported by the Spearman correlation (not significantly greater than zero). Also, a certain
Correlations of inter-industry wage differentials in deviation form estimated without and with controls for human capital (one-sided p-values in parentheses)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Canada</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pearson:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>without</td>
<td>0.964</td>
<td>0.968</td>
<td>0.702</td>
<td>0.752</td>
</tr>
<tr>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>with</td>
<td>0.794</td>
<td>0.847</td>
<td>0.710</td>
<td>0.546</td>
</tr>
<tr>
<td>(0.005)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spearman:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>without</td>
<td>0.983</td>
<td>0.933</td>
<td>0.717</td>
<td>0.633</td>
</tr>
<tr>
<td>(0.0005)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>with</td>
<td>0.533</td>
<td>0.550</td>
<td>0.750</td>
<td>0.433</td>
</tr>
<tr>
<td>(0.10)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Australia</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pearson:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>without</td>
<td>0.959</td>
<td>0.641</td>
<td>0.731</td>
<td></td>
</tr>
<tr>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>with</td>
<td>0.953</td>
<td>0.465</td>
<td>0.714</td>
<td></td>
</tr>
<tr>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spearman:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>without</td>
<td>0.917</td>
<td>0.650</td>
<td>0.583</td>
<td></td>
</tr>
<tr>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>with</td>
<td>0.917</td>
<td>0.383</td>
<td>0.667</td>
<td></td>
</tr>
<tr>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Germany</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pearson:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>without</td>
<td>0.707</td>
<td>0.825</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.026)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>with</td>
<td>0.574</td>
<td>0.747</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.053)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spearman:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>without</td>
<td>0.750</td>
<td>0.700</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.025)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>with</td>
<td>0.467</td>
<td>0.533</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.25)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* For each country and each correlation, wage differentials in deviation form, \( D_i = \bar{\delta}_i - \bar{\delta} \), are available for 9 sectors.

*1-tailed tests of the null hypothesis \( H_0: \rho = 0 \) against the alternative hypothesis \( H_1: \rho > 0 \). The relevant claim is, in fact, that the international wage structure is stable across countries. Only positive correlations are therefore expected. The tests for Pearson correlations are based on the \( t \)-transformation suggested by Kendall and Stuart (1977, p.416, §16.28):

\[
t = \frac{(n-2)\hat{\rho}^2(1-\hat{\rho}^2))^{1/2}}{\sqrt{(1-\hat{\rho}^2)}}
\]

which, under the null hypothesis, follows a \( t \) distribution with \( (n-2) \) degrees of freedom. The tests for Spearman correlations are based on Zar's distribution table (Zar, 1972, p.579).
similarity exists between Germany and the Netherlands in terms of rank correlation, significantly greater than zero at the 0.5% level, but this is not confirmed by the Pearson correlation (not significantly greater than zero). This seems a result worth emphasizing, namely that Germany and the Netherlands are not very similar to each other, at least much less than the United States and Canada. So a simple view of a North American versus a European pattern does not seem to hold. All the other correlations are rather small and insignificant. They are also quite far from the values obtained by other authors with aggregate data (Krueger and Summers, 1987; Gittleman and Wolff, 1993), presented and discussed in Chapter 3, and summarized in the following table:

<table>
<thead>
<tr>
<th></th>
<th>Canada</th>
<th>Australia</th>
<th>Germany</th>
<th>Netherlands</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggregate data, Krueger and Summers*</td>
<td>0.92</td>
<td>–</td>
<td>0.85</td>
<td>–</td>
</tr>
<tr>
<td>Aggregate data, Gittleman and Wolff*</td>
<td>0.82</td>
<td>0.82</td>
<td>0.86</td>
<td>0.86</td>
</tr>
<tr>
<td>Micro data, without controls*</td>
<td>0.96</td>
<td>0.97</td>
<td>0.70</td>
<td>0.75</td>
</tr>
<tr>
<td>Micro data, with controls*</td>
<td>0.79</td>
<td>0.85</td>
<td>0.71</td>
<td>0.55</td>
</tr>
<tr>
<td>Canada</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggregate data, Krueger and Summers*</td>
<td>–</td>
<td>–</td>
<td>0.83</td>
<td>–</td>
</tr>
<tr>
<td>Micro data, without controls*</td>
<td>0.96</td>
<td>0.64</td>
<td>0.73</td>
<td></td>
</tr>
<tr>
<td>Micro data, with controls*</td>
<td>0.95</td>
<td>0.47</td>
<td>0.71</td>
<td></td>
</tr>
</tbody>
</table>

*Source:* Krueger and Summers (1987, p.26, Table 2.3). Data refer to 1982 and manufacturing industries only.

*Source:* Gittleman and Wolff (1993, p.303, Table 4). Data refer to 1985 and all industries.

*Source:* Table 5.4 (this Chapter). Data refer to 1985-87 and all industries.

The degree of similarity between inter-industry wage structures even tends to reduce when controls for human capital and socio-demographic characteristics are introduced in the wage equations. The results in Table 5.4 for the differentials estimated with controls show that, with a very few exceptions (the Pearson and the Spearman correlations between the United States and Germany, and the Spearman correlation between Canada and the Netherlands), the correlation coefficients decrease with respect to the values calculated for differentials estimated without controls, sometimes considerably. Pearson correlations remain significantly greater than zero at the 0.5% level for the United States and Canada, the United States and Australia, Canada and Australia. The Spearman correlation continues to be significant only in the case of Canada and Australia. All the other correlations are insignificant at the 0.5% level and they also become considerably smaller than those derived

57 Reductions range from 0.7% to 27.5% for the Pearson correlations and from 0% to 45.8% for the Spearman correlations.
from aggregate data - with the only exception of the Pearson correlation between the United States and Australia, the value of which is comparable with the result obtained by Gittleman and Wolff (1993). The magnitude of such correlations across countries tends to be overstated in aggregate data, since a certain proportion of these similarities seem to be due to correlations of the structure of labour quality across countries (Edin and Zetterberg, 1992). These findings also seem to confirm that the American, Canadian, and Australian wage structures are less affected than others by differences in human capital and socio-demographic characteristics, a phenomenon that calls for an explanation based on institutional aspects of wage determination, as argued in the previous section.

Cross-country comparisons made through correlation coefficients between estimated differentials are not totally correct from a statistical point of view, even if they provide some intuitions about the underlying phenomena. The values in the vectors of wage differentials used to calculate such correlations are not, in fact, randomly extracted observations from a bivariate normal population - the implicit condition for the construction of correlation coefficients - but the outcomes of OLS estimates of a regression model, which entail a least squares sampling error. Each differential is associated with a measure of the precision of its estimate (the OLS standard error), which is completely ignored in the procedure of computing simple correlations.

A possible method to solve this problem could consist in pooling the data for all five countries and estimating a single wage regression model with five distinct sets of industry dummies among the explanatory variables, generated as country×industry interaction terms. In order to assess the degree of similarity between inter-industry wage structures of different countries, an F-test for joint equality restrictions could then be easily performed on the sets of coefficients of the various industry dummy variables. In principle, the LIS database permits simultaneous access to multiple national data-sets. However, in practice, the indirect nature of the access to the data source imposes a limitation that prevents a LIS user from applying this approach. In the wage equation that includes control variables for human capital and socio-demographic conditions, it would be necessary to define a large number of country×control interaction terms, since the sets of controls are not identically defined for all countries (see Appendix 5.A). This raises the number of explanatory variables in the regression to 95, including the five sets of industry dummies. Such an amount, unfortunately,
exceeds the maximum number of explanatory variables that a LIS user may specify in a single regression statement\(^{58}\).

Moreover, an approach based on an \(F\)-test faces a serious conceptual limitation. It entails in fact a comparison between estimated industry dummies coefficients \(\delta_k\), and not between wage differentials in deviation form, \(D_k = \delta_k - \bar{\delta}\), and a low degree of similarity between coefficients does not necessarily imply that the same condition is satisfied in terms of differentials in deviation form. This point can be illustrated with a simple example. Industry dummy coefficients represent wage differences with respect to the base sector excluded from the regression (say, agriculture). Assume that there are only two countries to be compared, indicated as A and B. Suppose that country A presents large estimated wage differences with respect to the base sector, but that these differences are all equal among them (all sectors pay equal wages, apart from agriculture). Suppose that country B, instead, presents very small wage differences for all sectors with respect to the base sector, which implies that these differences are very similar among them (all sectors pay equal wages, included agriculture). If I compare the two vectors of coefficients through an \(F\)-test, the null hypothesis of identical wage structures is likely to be rejected, given the different size of the coefficients for country A and B. Notice that agriculture is not considered here, because its coefficient is not defined. However, if I calculate wage differentials in deviation form for country A, they turn out to be relatively small, because the employment-weighted mean differential in country A is large (especially if agriculture has a small weight in terms of employment, as it is the case for all the countries considered in my analysis). This is true from all sectors apart from agriculture, which is considered here and which presents a large differential equal to minus the employment-weighted mean differential. Also for country B all differentials in deviation form (included that of agriculture) turn out to be small, because the employment-weighted mean of small differentials is also small. If I compare the two vectors of differentials in deviation form, they tend to indicate the existence of a higher degree of similarity between wage structures than that expressed by estimated coefficients. And this is precisely the type of similarity which is relevant in the present context. On the other hand, if estimated

\(^{58}\) Note that this limit to the number of explanatory variables that may enter a regression statement is not imposed by the package \textit{SPSS-X}, but by the LIS administrators.
coefficients are similar enough to be unable to reject the null hypothesis of identical inter-industry wage structures across countries through an \( F \)-test of equality restrictions. The same hypothesis will be necessarily accepted in terms of differentials in deviation form. An \( F \)-test on coefficients, therefore, implies testing an hypothesis of similarity in a more restrictive sense, because similarity is defined relative to an arbitrarily chosen base sector. Wage differentials in deviation form, instead, represent inter-industry differences in an absolute sense, independent of the choice of the base sector in the regression.

5.4.2 Minimum Distance Chi-Square Tests

An alternative method to implement statistically rigorous comparisons between wage structures consists in a \( \chi^2 \) test based on the minimum distance estimation technique. This approach overcomes both the difficulty raised by the correlation coefficient, since it takes the precision of OLS estimates into account, and the limitations of an \( F \)-test on coefficients from a pooled regression, because it applies directly to differentials in deviation form and requires just the estimated industry coefficients of each separate country and their OLS variance-covariance matrices. Estimated coefficients \( \hat{\delta}_k \) are converted into differentials in deviation form, \( D_k^* = \hat{\delta}_k - \bar{\delta} \), and variance-covariance matrices are transformed accordingly, following the procedure illustrated in the general Appendix to the thesis.

From the technique of minimum distance estimation (illustrated in its general principles in Appendix 5.E), I can derive a test for cross-country equality restrictions on vectors of wage differentials estimated in independent regressions. Let \( m \) be the number of countries involved in the comparison and \( p \) the number of industry differentials available for each country. Imposing equality restrictions on wage differentials implies:

\[
\pi = R\theta \tag{5.3}
\]

where \( \pi \) is a \((mp \times 1)\) vector constructed as the stack of the \( p \) true differentials of the \( m \) countries, \( R \) is a \((mp \times p)\) matrix constructed as the stack of \( m \) identity matrices each of
dimensions \((p \times p)\), and \( \theta \) is a \((p \times 1)\) vector of unknown parameters. The set of linear restrictions simply means that if the vectors of wage differentials are equal across countries, they are all equal to \( \theta \). This represents the null hypothesis of the test for equality restrictions.

From my regression analysis, I obtain the OLS coefficients used to construct the estimator \( \hat{\pi} \) of the parameter vector \( \pi \) of wage differentials in deviation form. The minimum distance estimation of the unknown parameter vector \( \theta \) consists in choosing \( \theta \) to minimize the function:

\[
C(\theta) = (\hat{\pi} - R\theta)'\hat{\Omega}^{-1}(\hat{\pi} - R\theta)
\]  

(5.4)

where \( \hat{\Omega}^{-1} \) is a \((mp \times mp)\) block-diagonal matrix with the inverses of the OLS estimated variance-covariance matrices of the wage differentials contained in \( \hat{\pi} \) - a block for each country - on the diagonal. As already said, \( \hat{\pi} \) being a vector of wage differentials in deviation form, the OLS variance-covariance matrices used to build \( \hat{\Omega}^{-1} \) are transformed accordingly.

The properties of the minimum distance estimator (see Appendix 5.E) imply that the solution to this minimization problem is provided by the generalized least squares estimator of \( \theta \):

\[
\hat{\theta} = (R'\hat{\Omega}^{-1}R)^{-1}R'\hat{\Omega}^{-1}\hat{\pi}.
\]  

(5.5)

The same set of properties also implies that, under the null hypothesis, the minimized value of the objective function, \( C(\hat{\theta}) \), has a limiting \( \chi^2 \) distribution with \((m-1)p\) degrees of freedom.

To summarize, the testing procedure consists of the following two steps: first, I calculate the GLS estimator \( \hat{\theta} \) using the transformation in deviation form of my OLS

59 The fairly reasonable assumption of no covariance of wage differentials among different countries implies the block-diagonal form.
estimates for \( \hat{\pi} \) and the blocks of \( \hat{\Omega}^{-1} \): second, I compute the minimized value of the function \( C(\hat{\theta}) \) using again transformed OLS estimates for \( \hat{\pi} \) and \( \hat{\Omega}^{-1} \) and substituting \( \Theta \) with the estimate \( \hat{\Theta} \) obtained in the first step. The resulting \( \chi^2 \) statistic can then be compared with \( \chi^2 \) critical values at appropriate significance levels. If the computed statistic exceeds the critical values, the null hypothesis of equal wage differentials across countries is rejected and counties have to be regarded as different in terms of their inter-industry wage structure. If, instead, the computed \( \chi^2 \) is smaller than the critical values, I fail to reject the null hypothesis and the inter-industry wage structure can be viewed as perfectly similar across countries.

No existing statistical package performs the minimum distance \( \chi^2 \) test automatically. For this purpose, I have therefore developed a program using the package MATLAB\(^{63}\). The structure of the MATLAB procedure employed is reported in Appendix 5.F. Table 5.5 presents the results obtained with this test based on the minimum distance approach. I consider the vectors of wage differentials in deviation form, \( D^*_k = \delta_k - \bar{\delta} \), estimated both without and with control variables for human capital and socio-demographic characteristics, as they appear in Table 5.2 and Table 5.3 respectively. Moreover, I test both the joint hypothesis of identical wage structures in all five countries simultaneously and the less restrictive hypothesis of equality of wage differentials for any possible pair of countries.

In all cases, the outcome of the \( \chi^2 \) test implies the rejection of the null hypothesis of identical inter-sectoral wage structures at a very strong significance level. The extremely small p-values shown in the third column of Table 5.5 indicate little credibility for the null hypotheses, both when differentials are estimated without controls for human capital and when they are estimated with such controls. Differently from the case of correlations, the introduction of control variables in the wage regressions has a mixed effect on computed \( \chi^2 \) statistics: for the joint hypothesis on all five countries, it reduces the value of \( \chi^2 \); for the less restrictive hypotheses on pairs of countries, it increases the \( \chi^2 \) values in half of the cases and reduces them in the other half. Therefore, it seems no longer so evident that the degree of

\(^{63}\) The version of the statistical package used is 386-MATLAB, Ver. 3.5j.
TABLE 5.5
Minimum distance $\chi^2$ tests of equality restrictions on interindustry wage structures: wage differentials in deviation form

<table>
<thead>
<tr>
<th>Null hypothesis</th>
<th>Computed $\chi^2$ statistic*</th>
<th>$P$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Wage differentials estimated without controls for human capital</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$D'<em>{US} = D'</em>{CANADA} = D'<em>{AUSTRALIA} = D'</em>{GERMANY} = D'_{NETHERLANDS}$</td>
<td>$\chi^2(36) = 865.31$</td>
<td>$0.3220 \times 10^{11}$</td>
</tr>
<tr>
<td>$D'<em>{US} = D'</em>{CANADA}$</td>
<td>$\chi^2(9) = 158.36$</td>
<td>$0.3220 \times 10^{11}$</td>
</tr>
<tr>
<td>$D'<em>{US} = D'</em>{AUSTRALIA}$</td>
<td>$\chi^2(9) = 221.16$</td>
<td>$0.3220 \times 10^{11}$</td>
</tr>
<tr>
<td>$D'<em>{US} = D'</em>{GERMANY}$</td>
<td>$\chi^2(9) = 122.38$</td>
<td>$0.3220 \times 10^{11}$</td>
</tr>
<tr>
<td>$D'<em>{US} = D'</em>{NETHERLANDS}$</td>
<td>$\chi^2(9) = 122.68$</td>
<td>$0.3220 \times 10^{11}$</td>
</tr>
<tr>
<td>$D'<em>{CANADA} = D'</em>{AUSTRALIA}$</td>
<td>$\chi^2(9) = 50.43$</td>
<td>$0.1619 \times 10^{8}$</td>
</tr>
<tr>
<td>$D'<em>{CANADA} = D'</em>{GERMANY}$</td>
<td>$\chi^2(9) = 49.74$</td>
<td>$0.2459 \times 10^{8}$</td>
</tr>
<tr>
<td>$D'<em>{CANADA} = D'</em>{NETHERLANDS}$</td>
<td>$\chi^2(9) = 82.00$</td>
<td>$0.3220 \times 10^{11}$</td>
</tr>
<tr>
<td>$D'<em>{AUSTRALIA} = D'</em>{GERMANY}$</td>
<td>$\chi^2(9) = 64.14$</td>
<td>$0.2967 \times 10^{12}$</td>
</tr>
<tr>
<td>$D'<em>{AUSTRALIA} = D'</em>{NETHERLANDS}$</td>
<td>$\chi^2(9) = 41.33$</td>
<td>$0.3378 \times 10^{8}$</td>
</tr>
<tr>
<td>$D'<em>{GERMANY} = D'</em>{NETHERLANDS}$</td>
<td>$\chi^2(9) = 34.06$</td>
<td>$0.8726 \times 10^{4}$</td>
</tr>
<tr>
<td><strong>Wage differentials estimated with controls for human capital</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$D'<em>{US} = D'</em>{CANADA} = D'<em>{AUSTRALIA} = D'</em>{GERMANY} = D'_{NETHERLANDS}$</td>
<td>$\chi^2(36) = 614.98$</td>
<td>$0.3220 \times 10^{11}$</td>
</tr>
<tr>
<td>$D'<em>{US} = D'</em>{CANADA}$</td>
<td>$\chi^2(9) = 118.52$</td>
<td>$0.3220 \times 10^{11}$</td>
</tr>
<tr>
<td>$D'<em>{US} = D'</em>{AUSTRALIA}$</td>
<td>$\chi^2(9) = 133.64$</td>
<td>$0.3220 \times 10^{11}$</td>
</tr>
<tr>
<td>$D'<em>{US} = D'</em>{GERMANY}$</td>
<td>$\chi^2(9) = 150.48$</td>
<td>$0.3220 \times 10^{13}$</td>
</tr>
<tr>
<td>$D'<em>{US} = D'</em>{NETHERLANDS}$</td>
<td>$\chi^2(9) = 109.29$</td>
<td>$0.3220 \times 10^{11}$</td>
</tr>
<tr>
<td>$D'<em>{CANADA} = D'</em>{AUSTRALIA}$</td>
<td>$\chi^2(9) = 134.31$</td>
<td>$0.3220 \times 10^{13}$</td>
</tr>
<tr>
<td>$D'<em>{CANADA} = D'</em>{GERMANY}$</td>
<td>$\chi^2(9) = 76.55$</td>
<td>$0.3220 \times 10^{13}$</td>
</tr>
<tr>
<td>$D'<em>{CANADA} = D'</em>{NETHERLANDS}$</td>
<td>$\chi^2(9) = 68.63$</td>
<td>$0.3220 \times 10^{13}$</td>
</tr>
<tr>
<td>$D'<em>{AUSTRALIA} = D'</em>{GERMANY}$</td>
<td>$\chi^2(9) = 38.01$</td>
<td>$0.1738 \times 10^{4}$</td>
</tr>
<tr>
<td>$D'<em>{AUSTRALIA} = D'</em>{NETHERLANDS}$</td>
<td>$\chi^2(9) = 51.86$</td>
<td>$0.6787 \times 10^{-4}$</td>
</tr>
<tr>
<td>$D'<em>{GERMANY} = D'</em>{NETHERLANDS}$</td>
<td>$\chi^2(9) = 42.05$</td>
<td>$0.2240 \times 10^{6}$</td>
</tr>
</tbody>
</table>

* The wage differentials in deviation form, $D'_{s} = \delta_{s} - \bar{\delta}$, used for the present tests are those appearing in Table 5.2 (estimated without controls) and Table 5.3 (estimated with controls).

* The 5% critical points are $\chi^2_{0.05}(36)=51.00$ and $\chi^2_{0.05}(9)=16.92$; the 1% critical points are $\chi^2_{0.01}(36)=58.62$ and $\chi^2_{0.01}(9)=21.67$. 

261
similarity between wage structures tends to reduce when controls are introduced, a phenomenon that would be supported instead by a generalized increase in the values of \( \chi^2 \)'s. This is due to the fact that, unlike the simple correlation coefficient, the minimum distance \( \chi^2 \) test takes into account both the size of wage differentials and the precision with which they are estimated, assigning a smaller weight to differentials estimated with less precision. This type of evidence, however, should not be regarded as totally conclusive. The values of computed \( \chi^2 \) statistics are in fact so large that, if we consider the results of the tests in terms of p-values, the introduction of control variables has indeed the effect of generally reducing the plausibility of the null hypotheses: comparing the p-values in the first and in the second part of Table 5.5, we can see that when controls are introduced these values decrease or remain unchanged, with the only exception of the test involving Australia and Germany.

It is worth noting that a test of the described nature corresponds to testing the hypothesis of true correlations between wage structures being exactly equal to one. This is a limitation of the minimum distance \( \chi^2 \) approach, since the relevant claim to be tested is not that of absolutely identical inter-industry differentials, but rather that of a certain degree of similarity of wage structures across countries. The considerations proposed about the p-values for the tests, interpreted as a way to summarize what the data can say about the credibility of each null hypothesis, do not overcome such limitation, because p-values depend crucially on the type of hypothesis under test. For this reason I have previously presented also the traditionally computed correlation coefficients, which can provide an idea of the degree of similarity between countries on a more continuous scale. However, the very high significance level at which the null hypotheses are rejected in the \( \chi^2 \) tests casts some doubts on the reliability of the high correlations obtained by other authors with aggregate data and discussed in Chapter 3.

5.5 Conclusions

In this Chapter I have presented additional empirical evidence concerning the international pattern of inter-industry wage structures. The analysis has been based on the LIS data-bank, which, despite a certain number of limitations, represents a particularly suitable
source for cross-country comparisons. The availability of micro data for several countries through a single source allows comparative analyses that would otherwise be extremely onerous. Moreover, the fair degree of homogeneity achieved in the selection of data-sets and sub-samples and in the construction of the variables entering the regression model permits to reduce the heterogeneity problem encountered in Chapter 4 and to increase the reliability of international comparisons.

The existence of considerable differences among countries, already emerged in Chapter 4, seems to be confirmed by the present results. Inter-industry wage differentials are estimated for 5 countries: the United States, Canada, Australia, Germany, and the Netherlands. Raw-wage differentials, estimated without controlling for human capital and socio-demographic differences, already show significant dissimilarities. In terms of size, statistical significance and variability of differentials, the United States and Canada exhibit similar results, with high, highly significant and highly variable differentials; Germany and the Netherlands present instead lower, less significant and less variable differentials; Australia ranks as an intermediate case.

The degree of similarity among countries is even smaller when inter-industry wage differentials estimated with controls for human capital and socio-demographic characteristics are considered. The United States and Canada continue to exhibit differentials which are substantial in size, significance and variability; Germany and the Netherlands present small differentials which are seldom significant and whose variability is close to zero; Australia still represents an intermediate case.

The relative impact of human capital and socio-demographic controls on the estimated inter-industry wage structure also varies across countries. This impact is limited for the United States and Canada, substantial for Germany and the Netherlands, and mixed for Australia. All theses results seem to confirm the existence of a ranking among countries which reflects the institutional conditions of the various national labour markets, in particular the degree of centralization of wage bargaining procedures discussed in Chapter 2.

The actual degree of similarity of inter-industry wage structures across countries is then evaluated by means of correlation analysis and minimum distance $\chi^2$ tests. Correlation coefficients show a certain similarity between the United States, Canada and Australia, but a clear dissimilarity of these countries from Germany and the Netherlands, and of Germany and the Netherlands between them. This seems to militate against a simple view of a North
American versus a European pattern. Correlation coefficients are generally smaller when human capital and socio-demographic controls are taken into account. All correlations are also considerably smaller than those derived from aggregate data and presented in Chapter 3. Finally, minimum distance $\chi^2$ tests lead to the rejection of the null hypothesis of identical wage structures across countries at a very strong significance level. These findings again seem to confirm the importance of institutional aspects in wage determination.
Appendix 5.A: LIS Variables Involved in the Selection of the Sub-Samples and in the Construction of the Regression Variables

UNITED STATES

1) Sub-sample selection

Variable \( \text{PSEX} = \text{PERSON SEX} \)

1 = MALE
2 = FEMALE

Selected group: \( \text{PSEX} = 1 \)

Variable \( \text{PAGE} = \text{PERSON AGE} \)

Selected group: \( \text{PAGE} \geq 15 \)

Variable \( \text{PLFS} = \text{PERSON LABOUR FORCE STATUS} \)

1 = EMPLOYED AND WORKING
2 = EMPLOYED NOT AT WORK
3 = UNEMPLOYED
4 = KEEPING HOUSE, N.I.L.F.
5 = GOING TO SCHOOL, N.I.L.F.
6 = ILL DISABLED, N.I.L.F.
7 = OTHER, N.I.L.F.

Selected group: \( \text{PLFS} = 1 \)

Variable \( \text{PTYPEWK} = \text{PERSON TYPE (STATUS) OF WORKER} \)

0 = NONWORKER
1 = WAGE/SALARY
2 = SELF-EMPLOYED AGRIC.
3 = UNPAID AGRIC.
4 = PRIVATE HH. NON AGRIC.
5 = OTHER PRIVATE NON AGRIC.
6 = GOVERNMENT
7 = SELF-EMPLOYED NON AGRIC.
8 = UNPAID NON AGRIC.
Selected groups: \( PTYPEWK = 1.4.5 \)

Variables

- \( PWEEKFT = \) PERSON WEEKS WORKED FULL TIME
- \( PWEEKPT = \) PERSON WEEKS WORKED PART TIME
- \( PWEEKUP = \) PERSON WEEKS UNEMPLOYED

Selected group: \( PWEEKFT = 52 \) OR \( PWEEKPT = 52 \)

- \( PWEEKUP = 0 \)

Variable \( PGWAGE = \) PERSON GROSS WAGE/SALARY

Selected group: \( PGWAGE > 0 \)

Variable \( PHOURS = \) PERSON HOURS WORKED PER WEEK

Selected group: \( PHOURS > 0 \)

Variable \( WPERH = \frac{PGWAGE}{52*PHOURS} = \) PERSON HOURLY WAGE/SALARY

Selected group: \( 1 < WPERH \leq 250 \)

2) Construction of human capital and socio-demographic controls

**Age:**

Variable \( PAGE = \) PERSON AGE

Constructed variables:

- \( AGE = PAGE \)
- \( AGESQ = PAGE^2 \)

**Education:**

Variable \( PEDUC = \) PERSON EDUCATIONAL LEVEL

- 1 = NO SCHOOLING
- 2 = 1 YEAR OF EDUCATION
- 3 = 2 YEARS OF EDUCATION
- 4 = 3 YEARS OF EDUCATION
- 5 = 4 YEARS OF EDUCATION
- 6 = 5 YEARS OF EDUCATION
- 7 = 6 YEARS OF EDUCATION
- 8 = 7 YEARS OF EDUCATION
- 9 = 8 YEARS OF EDUCATION

266
10 = 9 YEARS OF EDUCATION
11 = 10 YEARS OF EDUCATION
12 = 11 YEARS OF EDUCATION
13 = 12 YEARS OF EDUCATION
14 = 13 YEARS OF EDUCATION
15 = 14 YEARS OF EDUCATION
16 = 15 YEARS OF EDUCATION
17 = 16 YEARS OF EDUCATION
18 = 17 YEARS OF EDUCATION
19 = 18 YEARS OR MORE

<table>
<thead>
<tr>
<th>Constructed dummies:</th>
<th>DEDUC1: PEDUC = 2.3.4.5.6.7 (base group)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DEDUC2: PEDUC = 8.9</td>
</tr>
<tr>
<td></td>
<td>DEDUC3: PEDUC = 10.11.12</td>
</tr>
<tr>
<td></td>
<td>DEDUC4: PEDUC = 13</td>
</tr>
<tr>
<td></td>
<td>DEDUC5: PEDUC = 14.15.16</td>
</tr>
<tr>
<td></td>
<td>DEDUC6: PEDUC = 17</td>
</tr>
<tr>
<td></td>
<td>DEDUC7: PEDUC = 18.19</td>
</tr>
<tr>
<td></td>
<td>DEDUCMIS: PEDUC = 1</td>
</tr>
</tbody>
</table>

**Marital status:**

<table>
<thead>
<tr>
<th>Variable</th>
<th>PMART = PERSON MARITAL STATUS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>MARRIED SPOUSE PRESENT</td>
</tr>
<tr>
<td>2</td>
<td>MARRIED AF. SPOUSE ABSENT (no cases)</td>
</tr>
<tr>
<td>3</td>
<td>MARRIED SPOUSE ABSENT</td>
</tr>
<tr>
<td>4</td>
<td>WIDOWED</td>
</tr>
<tr>
<td>5</td>
<td>DIVORCED</td>
</tr>
<tr>
<td>6</td>
<td>SEPARATED</td>
</tr>
<tr>
<td>7</td>
<td>NEVER MARRIED</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Constructed dummies:</th>
<th>DMART1: PMART = 7 (base group)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DMART2: PMART = 1.3</td>
</tr>
<tr>
<td></td>
<td>DMART3: PMART = 4</td>
</tr>
<tr>
<td></td>
<td>DMART4: PMART = 5</td>
</tr>
<tr>
<td></td>
<td>DMART5: PMART = 6</td>
</tr>
</tbody>
</table>

**Skill:**

<table>
<thead>
<tr>
<th>Variable</th>
<th>POCC = PERSON OCCUPATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>NONWORKER (excluded)</td>
</tr>
<tr>
<td>1</td>
<td>MANAGERS PUBLIC ADMIN.</td>
</tr>
<tr>
<td>2</td>
<td>MANAGERS/ADMIN. OTHER (no cases)</td>
</tr>
<tr>
<td>3</td>
<td>MANAGERS OTHER SALARY</td>
</tr>
<tr>
<td>4</td>
<td>MANAGERS OTHER SELF-EMP. (excluded)</td>
</tr>
<tr>
<td>5</td>
<td>MANAGEMENT RELATED OCC.</td>
</tr>
</tbody>
</table>
6 = ACCOUNTANT/AUDITOR  
7 = ARCHITECTS/SURVEYORS  
8 = ENGINEERS OTHER  
9 = NAT. SCIENTIST/MATHEMAT.  
10 = COMPUTER ANALYST/SCIEN.  
11 = HEALTH DIAGNOSTIC  
12 = PHYSICIANS/DENTISTS  
13 = HEALTH ASSESS./TREATMENT  
14 = TEACHERS/LIBRAR./CONSEL.  
15 = TEACHERS ELEM./SECONDARY  
16 = OTHER PROFESSIONALS  
17 = HEALTH TECHNICIANS  
18 = ENGINEERS/SCIENCE TECH.  
19 = OTHER TECHNICIANS  
20 = SALES PROP./SUPERVISORS  
21 = SALES REPRESENTATIVES  
22 = OTHER SALES OCC.  
23 = COMPUTER EQUIPMENT OP.  
24 = SECRETARIES/STENO./TYPST.  
25 = FINANCIAL REC. PROCESS  
26 = OTHER ADMIN. SUPPORT  
27 = PRIVATE HH. WORKER (no cases)  
28 = PROTECTIVE SERVICE  
29 = FOOD SERVICE  
30 = HEALTH SERVICE  
31 = CLEANING/BLDG. SERVICE  
32 = PERSONAL SERVICE  
33 = FARM OPERATOR/MANAGER  
34 = FARM OCC. EXC. MANAGER  
35 = REL. AGRICULTURE OCC.  
36 = FORESTRY/FISHING  
37 = MECHANICS/REPAIRERS  
38 = CONSTRUCTION TRADES  
39 = CARPENTERS  
40 = PRECISION PROD. SUPER.  
41 = PRECISION METAL WORK.  
42 = OTHER PRECISION OCC.  
43 = MACHINE OPERATORS  
44 = FABRICATORS/ASSEMBLERS  
45 = PRODUCTION INSPECT./TEST  
46 = TRANSPORTATION OCC.  
47 = MATERIAL MOVING EQUIP.  
48 = CONSTRUCTION LABOURERS  
49 = MATERIAL HANDLERS  
50 = OTHER HANDLERS/HELPERS  
51 = OTHER LABOURERS  
52 = ARMED FORCES/MILITARY (excluded)
1) **Constructed dummies:**

DSKILL1: POCC = 28.29.30.31.32.34.35.36.37.38.39. 
48.49.50.51 (base group)

DSKILL2: POCC = 43.44.45.46.47

DSKILL3: POCC = 40.41.42

DSKILL4: POCC = 21.22.23.24.25.26

DSKILL5: POCC = 17.18.19

DSKILL6: POCC = 6.7.8.9.10.11.12.13.14.15.16

DSKILL7: POCC = 1.3.5.20.33

3) **Construction of industry dummies**

Variable **PIND = PERSON INDUSTRY**

- 0 = NONWORKER (excluded)
- 1 = AGRICULTURE
- 2 = MINING
- 3 = CONSTRUCTION
- 4 = MANUF. LUMBER/WOOD PROD.
- 5 = MANUF. FURNITURE/FIXTURE
- 6 = MANUF. STONE/CLAY
- 7 = MANUF. PRIMARY METALS
- 8 = MANUF. FABRICATED METALS
- 9 = MANUF. UNSPEC. METALS
- 10 = MANUF. MACHINERY EXC. ELEC.
- 11 = MANUF. ELEC. MACHINERY
- 12 = MANUF. AUTOS/EQUIPMENT
- 13 = MANUF. AIRCRAFT/AC. PARTS
- 14 = MANUF. OTHER TRANSPORT
- 15 = MANUF. PROF./PHOTO./WATCH.
- 16 = MANUF. TOY/SPORTS/AMUS.
- 17 = MANUS. MISCELL. DURABLES
- 18 = MANUF. FOOD/KINDRED PROD.
- 19 = MANUF. TOBACCO
- 20 = MANUF. TEXTILE MILL PROD.
- 21 = MANUF. APPAREL/FINISH. TX.
- 22 = MANUF. PAPER/ALLIED PROD.
- 23 = MANUF. PRINTING/PUBLISH.
- 24 = MANUF. CHEMICAL/ALLIED
- 25 = MANUF. PETROLEUM/COAL
- 26 = MANUF. RUBBER/PLASTICS
- 27 = MANUF. LEATHER PRODUCTS
- 28 = TRANSPORTATION
- 29 = COMMUNICATIONS
- 30 = UTILITIES/SANITARY SER.
- 31 = WHOLESALE TRADE
- 32 = RETAIL TRADE
33 = FINANCE/INS./REAL ESTATE  
34 = BANKING/OTHER FINANCE  
35 = PRIVATE HH. SERVICES  
36 = BUSINESS SERVICES  
37 = REPAIR SERVICES  
38 = PERSONAL SERVICES  
39 = ENTERTAINMENT/RECREATION  
40 = HOSPITALS  
41 = OTHER HEALTH SERVICES  
42 = EDUCATIONAL SERVICES  
43 = SOCIAL SERVICES  
44 = OTHER PROF. SERVICES  
45 = FORESTRY/FISHERIES  
46 = PUBLIC ADMINISTRATION  
47 = ARMED FORCES/MILITARY (excluded)

Constructed dummies:  
DIND1: PIND = 1.45 (base group)  
DIND2: PIND = 2  
DIND3: PIND = 4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27  
DIND4: PIND = 30  
DIND5: PIND = 3  
DIND6: PIND = 31,32,37  
DIND7: PIND = 28.29  
DIND8: PIND = 33,34,36  
DIND9: PIND = 35,38,39,40,41,42,43,44,46

CANADA

1) Sub-sample selection

Variable PSEX = PERSON SEX  
1 = MALE  
2 = FEMALE

Selected group: PSEX = 1

Variable PAGE = PERSON AGE

Selected group: PAGE ≥ 15
Variable PLFS = PERSON LABOUR FORCE STATUS

1 = EMPLOYED
2 = UNEMPLOYED
3 = NOT IN LABOUR FORCE

Selected group: PLFS = 1

Variable PTYPEWK = PERSON TYPE (STATUS) OF WORKER

1 = WAGE/SALARY PRIVATE
2 = WAGE/SALARY PUBLIC
3 = SELF-EMPLOYED
4 = UNPAID FAMILY WORKER
5 = NON WORKER NEVER WRKD.
6 = NON WORKER SINCE 1982

Selected groups: PTYPEWK = 1,2

Variable PWEEKFT = PERSON WEEKS WORKED FULL TIME
PWEEKPT = PERSON WEEKS WORKED PART TIME
PWEEKUP = PERSON WEEKS UNEMPLOYED

Selected group: PWEEKFT = 52 OR PWEEKPT = 52
PWEEKUP = 0

Variable PGWAGE = PERSON GROSS WAGE/SALARY

Selected group: PGWAGE > 0

Variable PHOURS = PERSON HOURS WORKED PER WEEK

Selected group: PHOURS > 0

Variable WPERH = PGWAGE/(52*PHOURS) = PERSON HOURLY WAGE/SALARY

Selected group: 1 < WPERH ≤ 320
2) Construction of human capital and socio-demographic controls

Age:
Variable  \( PAGE = \) PERSON AGE

Constructed variables:  
\[ \text{AGE} = PAGE \]  
\[ \text{AGESQ} = PAGE^2 \]

Education:
Variable  \( PEDUC = \) PERSON EDUCATIONAL LEVEL

<table>
<thead>
<tr>
<th>PEDUC</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>NO SCHOOLING</td>
</tr>
<tr>
<td>2</td>
<td>LESS THAN 10 YEARS</td>
</tr>
<tr>
<td>3</td>
<td>11 YEARS OF EDUCATION</td>
</tr>
<tr>
<td>4</td>
<td>12 YEARS OF EDUCATION</td>
</tr>
<tr>
<td>5</td>
<td>13 YEARS OF EDUCATION</td>
</tr>
<tr>
<td>6</td>
<td>SOME POST-SECONDARY</td>
</tr>
<tr>
<td>7</td>
<td>POST-SECONDARY DIPLOMA</td>
</tr>
<tr>
<td>8</td>
<td>UNIVERSITY DEGREE</td>
</tr>
</tbody>
</table>

Constructed dummies:  
\( \text{DEDUC1} : \text{PEDUC} = 2 \) (base group)  
\( \text{DEDUC2} : \text{PEDUC} = 3 \)  
\( \text{DEDUC3} : \text{PEDUC} = 4 \)  
\( \text{DEDUC4} : \text{PEDUC} = 5 \)  
\( \text{DEDUC5} : \text{PEDUC} = 6 \)  
\( \text{DEDUC6} : \text{PEDUC} = 7 \)  
\( \text{DEDUC7} : \text{PEDUC} = 8 \)  
\( \text{DEDUCMIS} : \text{PEDUC} = 1 \)

Marital status:
Variable  \( PMART = \) PERSON MARITAL STATUS

<table>
<thead>
<tr>
<th>PMART</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>MARRIED</td>
</tr>
<tr>
<td>2</td>
<td>NEVER MARRIED</td>
</tr>
<tr>
<td>3</td>
<td>OTHER MARITAL STATUS</td>
</tr>
</tbody>
</table>

Constructed dummies:  
\( \text{DMART1} : \text{PMART} = 2 \) (base group)  
\( \text{DMART2} : \text{PMART} = 1 \)  
\( \text{DMART3} : \text{PMART} = 3 \)

Skill:
Variable  \( POCC = \) PERSON OCCUPATION

<table>
<thead>
<tr>
<th>POCC</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>MANAGER/ADMINISTRATOR</td>
</tr>
</tbody>
</table>

272
2 = NATURAL/SOCIAL SCI.
3 = TEACHER/RELATED OCC.
4 = CLERICAL/RELATED OCC.
5 = SALES OCCUPATIONS
6 = SERVICE OCCUPATIONS
7 = FARM., FISH., FORESTRY
8 = MINING, PROCES., MACHINE
9 = PRODUCT FAB./REPAIR
10 = CONSTRUCTION TRADES
11 = TRANSPORT EQUIP. OPER.
12 = NON WORKER NEVER WRKD. (excluded)
13 = NON WORKER SINCE 1982 (excluded)

Constructed dummies:
DSKILL1: POCC = 7,9,10 (base group)
DSKILL2: POCC = 8,11
DSKILL3: POCC = 4,5,6
DSKILL4: POCC = 2,3
DSKILL5: POCC = 1

3) Construction of industry dummies

Variable PIND = PERSON INDUSTRY

1 = AGRICULTURE
2 = OTHER PRIMARY
3 = MANUFACTURE NONDURABLES
4 = MANUFACTURE DURABLES
5 = CONSTRUCTION
6 = TRANS./COMM./UTILITIES
7 = WHOLESALE TRADE
8 = RETAIL TRADE
9 = FINANCE/INS./REAL ESTATE
10 = COMMUNITY SERVICES
11 = PERSONAL SERVICES
12 = BUSINESS/MISC. SERVICES
13 = PUBLIC ADMINISTRATION
14 = NON WORKER SINCE 1982 (excluded)
15 = NON WORKER NEVER WRKD. (excluded)

Constructed dummies:
DIND1: PIND = 1 (base group)
DIND2: PIND = 2
DIND3: PIND = 3,4
DIND4: PIND = 10
DIND5: PIND = 5
DIND6: PIND = 7,8
DIND7: PIND = 6
DIND8: PIND = 9.12  
DIND9: PIND = 11.13

AUSTRALIA

1) Sub-sample selection

Variable PSEX = PERSON SEX
1 = MALE
2 = FEMALE
Selected group: PSEX = 1

Variable PAGE = PERSON AGE
Selected group: PAGE ≥ 15

Variable PLFS = PERSON LABOUR FORCE STATUS
1 = PERMANENT UNABLE TO WRK.
2 = STILL AT SCHOOL
3 = STUDYING FULL TIME
4 = UNPAID VOLUNTARY WRK.
5 = EMPLOYED FULL TIME
6 = EMPLOYED PART TIME
7 = UNEMPLOYED
8 = NOT IN LABOUR FORCE
Selected groups: PLFS = 5,6

Variable PTYPEWK = PERSON TYPE (STATUS) OF WORKER
0 = NONWORKER/MISSING
1 = WAGE/SALARY (EMPLOYEE)
2 = WAGE/SALARY (S.E. INC.)
3 = SELF EMPLOYED NOT INC.
4 = UNPAID FAMILY WORKER
Selected group: PTYPEWK = 1
Variable **POCC = PERSON OCCUPATION**

0 = NONWORKER
1 = MANAGERS/ADMINISTRATORS
2 = PROFESSIONALS
3 = PARA PROFESSIONALS
4 = TRADESPERSONS
5 = CLERKS
6 = STATESPERSON/PERS. SERV.
7 = PLANT/MACHINE OP./DRIVER
8 = LABOURERS/RELATED
9 = DEFENCE WORKERS

Selected groups: **POCC ≠ 9**

Variable **PWEKFT = PERSON WEEKS WORKED FULL TIME**
**PWEKPT = PERSON WEEKS WORKED PART TIME**
**PWEKUP = PERSON WEEKS UNEMPLOYED**

Selected group: **PWEKFT = 52 OR PWEKPT = 52**
**PWEKUP = 0**

Variable **PGWAGE = PERSON GROSS WAGE/SALARY**

Selected group: **PGWAGE > 0**

Variable **PHOURS = PERSON HOURS WORKED PER WEEK** (class intervals; then transformed into the mid-points variable **MYPHOURS**)

0 = NON WORKER
1 = UNDER 10 HOURS
2 = 10 TO 19 HOURS
3 = 20 TO 24 HOURS
4 = 25 TO 29 HOURS
5 = 30 TO 34 HOURS
6 = 35 TO 39 HOURS
7 = 40 TO 44 HOURS
8 = 45 TO 49 HOURS
9 = 50 HOURS OR MORE

Selected groups: **PHOURS ≠ 0**

Variable **WPERH = PGWAGE/(52*MYPHOURS)**
= PERSON HOURLY WAGE/SALARY

Selected group: \( 1 < \text{WPERH} \leq 365 \)

2) Construction of human capital and socio-demographic controls

**Age:**
Variable \( \text{PAGE} = \) PERSON AGE (mid-points of age classes)

Constructed variables:
- \( \text{AGE} = \text{PAGE} \)
- \( \text{AGESQ} = \text{PAGE}^2 \)

**Education:**
Variable \( \text{PEDUC} = \) PERSON EDUCATIONAL LEVEL

1 = STUDENT  
2 = NONQUALIFIED  
3 = COMP. HIGHEST YEAR SCNRY.  
4 = COMP. HIGHEST SINCE LVNG.  
5 = TRADE CERTIFICATE  
6 = OTHER CERTIFICATE  
7 = BACHELOR DEG. OR HIGHER  
8 = OTHER QUALIFICATION  
9 = NEVER WENT TO SCHOOL

Constructed dummies:
- \( \text{DEDUC1}: \text{PEDUC} = 1,2,8 \) (base group)  
- \( \text{DEDUC2}: \text{PEDUC} = 3,4 \)  
- \( \text{DEDUC3}: \text{PEDUC} = 5 \)  
- \( \text{DEDUC4}: \text{PEDUC} = 6 \)  
- \( \text{DEDUC5}: \text{PEDUC} = 7 \)  
- \( \text{DEDUCMIS}: \text{PEDUC} = 9 \)

**Marital status:**
Variable \( \text{PMART} = \) PERSON MARITAL STATUS

1 = MARRIED  
2 = SEPARATED/WIDOWED/DIVORCED  
3 = NEVER MARRIED

Constructed dummies:
- \( \text{DMART1}: \text{PMART} = 3 \) (base group)  
- \( \text{DMART2}: \text{PMART} = 1 \)  
- \( \text{DMART3}: \text{PMART} = 2 \)
Skill:
Variable POCC = PERSON OCCUPATION

0 = NONWORKER (excluded)
1 = MANAGERS/ADMINISTRATORS
2 = PROFESSIONALS
3 = PARA PROFESSIONALS
4 = TRADESPERSON
5 = CLERKS
6 = STATSPERSON/PERS. SERV.
7 = PLANT/MACHINE OP./DRIVER
8 = LABOURERS/RELATED
9 = DEFENCE WORKERS (excluded)

Constructed dummies:  
DSKILL1: POCC = 8 (base group)  
DSKILL2: POCC = 7  
DSKILL3: POCC = 4,5,6  
DSKILL4: POCC = 2,3  
DSKILL5: POCC = 1

3) Construction of industry dummies

Variable PIND = PERSON INDUSTRY

-1 = MISSING (no cases)
0 = NON WORKER (excluded)
1 = AGRICULTURE/FORESTRY
2 = MINING
3 = MANUFACTURING
4 = ELEC./GAS/WATER
5 = CONSTRUCTION
6 = WHOLESALE/RETAIL TRADE
7 = TRANSPORT/STORAGE
8 = COMMUNICATION
9 = FINANCE/PROP./BUSINESS
10 = PUBLIC ADMIN./DEFENCE (DEFENCE excluded)
11 = COMMUNITY SERVICES
12 = RECRE./PERS./OTHER SERV.
13 = OTHER (no cases)

Constructed dummies:  
DIND1: PIND = 1 (base group)  
DIND2: PIND = 2  
DIND3: PIND = 3  
DIND4: PIND = 4,11  
DIND5: PIND = 5  
DIND6: PIND = 6
DIND7: PIND = 7.8  
DIND8: PIND = 9  
DIND9: PIND = 10.12

GERMANY

1) Sub-sample selection

Variable  PSEX = PERSON SEX  
1 = MALE  
2 = FEMALE  
Selected group: PSEX = 1

Variable  PAGE = PERSON AGE  
Selected group: PAGE ≥ 15

Variable  PLFS = PERSON LABOUR FORCE STATUS  
0 = MISSING  
1 = NOT IN LABOUR FORCE  
2 = LOOKING OR ON LAYOFF  
3 = EMPLOYED CIVILIAN  
4 = GOING TO SCHOOL  
5 = MANDATORY MILITARY SER.  
6 = PROFESSIONAL SOLDIER  
Selected group: PLFS = 3

Variable  PTYPEWK = PERSON TYPE (STATUS) OF WORKER  
-1 = MISSING  
0 = NONWORKER/NOT APPLIC.  
1 = APPRENTICE  
2 = VOLUNTEER/TRAINEE  
11 = UNSKILLED WRK. PUBLIC  
12 = SEMI-SKILLED WRK. PUBLIC  
13 = SKILLED WRK./CRAFT. PUB.  
14 = FOREMAN PUBLIC SERVICE
15 = BUILDING FOREMAN PUBLIC
21 = UNSKILLED WRK. PRIVATE
22 = SEMI-SKILLED WRK. PRIV.
23 = SKILLED WRK./CRAFT. PRIV.
24 = FOREMAN PRIVATE SECTOR
25 = BUILDING FOREMAN PRIV.
31 = WHITE-COL. FOREMAN PUB.
32 = WHITE-COLLAR PUBLIC
33 = QUALIFIED WHITE-COL. PUB.
34 = HIGH QUAL. WHITE-COL. PUB.
35 = MANAGER WHITE-COL. PUB.
41 = WHITE-COL. FOREMAN PRIV.
42 = WHITE-COLLAR PRIVATE
43 = QUALIFIED WHITE-COL. PRIV.
44 = HIGH QUAL. WHITE-COL. PRIV.
45 = MANAGER WHITE-COL. PRIV.
51 = LOW-LEVEL PUB. SERVICE
52 = MID-LEVEL PUB. SERVICE
53 = HIGH-LEVEL PUB. SERVICE
54 = HIGH PUBLIC OFFICIAL
60 = INDEPENDENT FARMERS
70 = SELF-EMP./0-9 CO-WORKERS
81 = SELF-EMP./9 CO-WRK. OR +
82 = ACADEMIC PROFESSIONS
90 = ASSISTANCE FAMILY MEMB.

Selected groups: PTYPEWK = 11, 12, 13, 14, 15, 21, 22, 23, 24, 25, 31, 32, 33, 34, 35, 41, 42, 43, 44, 45

Variable

PWEWKFT = PERSON WEEKS WORKED FULL TIME
PWEKPT = PERSON WEEKS WORKED PART TIME
PWEKUP = PERSON WEEKS UNEMPLOYED

Selected group: PWEWKFT = 52 OR PWEKPT = 52
PWEKUP = 0

Variable

PGWAGE = PERSON GROSS WAGE/SALARY

Selected group: PGWAGE > 0

Variable

PHOURS = PERSON HOURS WORKED PER WEEK

Selected group: PHOURS > 0
Variable \( \text{WPERH} = \text{PGWAGE}/(52*\text{PHOURS}) = \text{PERSON HOURLY WAGE/SALARY} \)

Selected group: \( 1 < \text{WPERH} \leq 400 \)

2) Construction of human capital and socio-demographic controls

Age:
Variable \( \text{PAGE} = \text{PERSON AGE} \)

Constructed variables: \( \text{AGE} = \text{PAGE} \)
\( \text{AGESQ} = \text{PAGE}^2 \)

Education:
Variable \( \text{PEDUC} = \text{PERSON EDUCATIONAL LEVEL} \)

0 = MISSING
1 = ELEMENTARY SCHOOL
2 = VOCATIONAL SCHOOL
3 = TECHNICAL HIGH SCHOOL
4 = GENERAL HIGH SCHOOL
5 = OTHER EDUCATION

Constructed dummies: \( \text{DEDUC1}: \text{PEDUC} = 1 \) (base group)
\( \text{DEDUC2}: \text{PEDUC} = 2 \)
\( \text{DEDUC3}: \text{PEDUC} = 3 \)
\( \text{DEDUC4}: \text{PEDUC} = 4 \)
\( \text{DEDUC5}: \text{PEDUC} = 5 \)
\( \text{DEDUCMIS}: \text{PEDUC} = 0 \)

Marital status:
Variable \( \text{PMART} = \text{PERSON MARITAL STATUS} \)

1 = MARRIED
2 = SEPARATED
4 = WIDOWED
5 = DIVORCED
7 = NEVER MARRIED

Constructed dummies: \( \text{DMART1}: \text{PMART} = 7 \) (base group)
\( \text{DMART2}: \text{PMART} = 1 \)
\( \text{DMART3}: \text{PMART} = 2 \)
\( \text{DMART4}: \text{PMART} = 4 \)
\( \text{DMART5}: \text{PMART} = 5 \)
Skill: 
Variable 

PTYPEWK = PERSON TYPE (STATUS) OF WORKER

-1 = MISSING (excluded)
0 = NONWORKER/NOT APPLIC. (excluded)
1 = APPRENTICE (excluded)
2 = VOLUNTEER/TRAINEE (excluded)
11 = UNSKILLED WRK. PUBLIC
12 = SEMI-SKILLED WRK. PUBLIC
13 = SKILLED WRK./CRAFT. PUB.
14 = FOREMAN PUBLIC SERVICE
15 = BUILDING FOREMAN PUBLIC
21 = UNSKILLED WRK. PRIVATE
22 = SEMI-SKILLED WRK. PRIV.
23 = SKILLED WRK./CRAFT. PRIV.
24 = FOREMAN PRIVATE SECTOR
25 = BUILDING FOREMAN PRIV.
31 = WHITE-COL. FOREMAN PUB.
32 = WHITE-COLLAR PUBLIC
33 = QUALIFIED WHITE-COL. PUB.
34 = HIGH QUAL. WHITE-COL. PUB.
35 = MANAGER WHITE-COL. PUB.
41 = WHITE-COL. FOREMAN PRIV.
42 = WHITE-COLLAR PRIVATE
43 = QUALIFIED WHITE-COL. PRIV.
44 = HIGH QUAL. WHITE-COL. PRIV.
45 = MANAGER WHITE-COL. PRIV.
51 = LOW-LEVEL PUB. SERVICE (excluded)
52 = MID-LEVEL PUB. SERVICE (excluded)
53 = HIGH-LEVEL PUB. SERVICE (excluded)
54 = HIGH PUBLIC OFFICIAL (excluded)
60 = INDEPENDENT FARMERS (excluded)
70 = SELF-EMP./0-9 CO-WORKERS (excluded)
81 = SELF-EMP./9 CO-WRK. OR + (excluded)
82 = ACADEMIC PROFESSIONS (excluded)
90 = ASSISTANCE FAMILY MEMB. (excluded)

Constructed dummies: 
DSKILL1: PTYPEWK = 11,21 (base group)
DSKILL2: PTYPEWK = 12,22
DSKILL3: PTYPEWK = 13,23
DSKILL4: PTYPEWK = 14,24
DSKILL5: PTYPEWK = 15,25
DSKILL6: PTYPEWK = 31,41
DSKILL7: PTYPEWK = 32,42
DSKILL8: PTYPEWK = 33,43
DSKILL9: PTYPEWK = 34,44
DSKILL10: PTYPEWK = 35,45
3) Construction of industry dummies

Variable \( \text{PIND} = \text{PERSON INDUSTRY} \)

-1 = MISSING
0 = NONWORKER/NOT APPLIC.
1 = AGRIC./FOREST./HORTIC.
2 = FISH./ANIMAL HUSBANDRY
3 = POWER/WATER PRODUCTION
4 = MINING INDUSTRY
5 = MANUF. CHEMICAL/MINERAL
6 = MANUF. PLASTICS
7 = STONE/RELATED INDUSTRY
8 = MANUF. STEEL/METAL
9 = MANUF. MACHINE/CAR
10 = MANUF. ELECTRONICS
11 = MANUF. WOOD/PAPER
12 = MANUF. LEATHER/TEXTILE
13 = MANUF. FOOD
14 = CONSTRUCTION INDUSTRY
15 = CONSTRUCTION REL. TRADE
16 = WHOLESALE TRADE
17 = TRADING AGENCY
18 = RETAIL TRADE
19 = FEDERAL RAILWAYS
20 = FEDERAL POST ADMIN./BANK
21 = OTHER COMMUNICATION SER.
22 = FINANCIAL INSTITUTION
23 = INSURANCE EXC. SOCIAL
24 = CATERING/HOTEL/ACCOMMOD.
25 = PERSONAL SERVICES
26 = CLEANING/WASTE REMOVAL
27 = TEACHING/RESEARCH/ARTS
28 = PUBLIC HEALTH/HOSPITALS
29 = REAL ESTATE/RELATED SER.
30 = OTHER SERVICES
31 = NON-PROFIT ORG./CHURCH
32 = PRIVATE HOUSEHOLDS
33 = FED./REGION./LOCAL AUTHOR.
34 = SOCIAL SEC./LABOUR OFFIC.
35 = OTHER INDUSTRY

Constructed dummies:  
DIND1: PIND = 1,2 (base group)  
DIND2: PIND = 4  
DIND3: PIND = 5,6,7,8,9,10,11,12,13  
DIND4: PIND = 3,26  
DIND5: PIND = 14
NETHERLANDS

1) Sub-sample selection

Variable  **PSEX = PERSON SEX**

1 = MALE  
2 = FEMALE

Selected group:  PSEX = 1

Variable  **PAGE = PERSON AGE**

Selected group:  PAGE ≥ 15

Variable  **PLFS = PERSON LABOUR FORCE STATUS**

1 = NOT IN LABOUR FORCE  
2 = LOOKING FOR WORK  
3 = IN LABOUR FORCE  
4 = GOING TO SCHOOL

Selected group:  PLFS = 3

Variable  **PTYPEWK = PERSON TYPE (STATUS) OF WORKER**

0 = NONE, NOT APPLICABLE  
1 = PRIVATE  
2 = PUBLIC  
3 = NONPROFIT

Selected groups:  PTYPEWK = 1,2,3

Variable  **POCC = PERSON OCCUPATION**
0 = NONE. NOT APPLICABLE
1 = HOUSEHOLD
2 = STUDYING
3 = PENSION
4 = INVALID
5 = JOBLESS NOT SEARCH.
6 = JOBLESS SEARCHING
7 = WORKS TOGETHER WITH
8 = SELF-EMPLOYED
9 = EMPLOYEE

Selected group: POCC = 9

Variable PUNEMP = PERSON UNEMPLOYMENT COMPENSATION
Selected group: PUNEMP = 0

Variable PGWAGE = PERSON GROSS WAGE/SALARY
Selected group: PGWAGE > 0

Variable PHOURS = PERSON HOURS WORKED PER WEEK
Selected group: PHOURS > 0

Variable WPERH = PGWAGE/(52*PHOURS) = PERSON HOURLY WAGE/SALARY
Selected group: 1 < WPERH ≤ 445

2) Construction of human capital and socio-demographic controls

Age:
Variable PAGE = PERSON AGE

Constructed variables: AGE = PAGE
AGESQ = PAGE^2

Education:
Variable PEDUC = PERSON EDUCATIONAL LEVEL

0 = MISSING
1 = PRIMARY
2 = EXTENDED PRIMARY
3 = SECONDARY
4 = UNIVERSITY
5 = OTHERS (no cases)

Constructed dummies:  
DEDUC1: PEDUC = 1 (base group)
DEDUC2: PEDUC = 2
DEDUC3: PEDUC = 3
DEDUC4: PEDUC = 4
DEDUCMIS: PEDUC = 0

Marital status:
Variable PMART = PERSON MARITAL STATUS
0 = NONE, NOT APPLICABLE (no cases)
1 = MARRIED
2 = WIDOWED
3 = DIVORCED/SEPARATED
4 = UNMARRIED

Constructed dummies:  
DMART1: PMART = 4 (base group)
DMART2: PMART = 1
DMART3: PMART = 2
DMART4: PMART = 3

Skill:
Variable PTOCC = PERSON OCCUPATIONAL TRAINING
0 = NONE, NOT APPLICABLE
1 = LOWER
2 = SECONDARY
3 = HIGHER

Constructed dummies:  
DSKILL1: PTOCC = 0,1 (base group)
DSKILL2: PTOCC = 2
DSKILL3: PTOCC = 3

3) Construction of industry dummies

Variable PIND = PERSON INDUSTRY
0 = NONE, NOT APPLICABLE
1 = AGRICULTURE
2 = MINING  
3 = LIGHT INDUSTRY  
4 = HEAVY INDUSTRY  
5 = PUBLIC UTIL.  
6 = CONSTRUCTION  
7 = TRADE, REPAIR  
8 = COMMUNICATION  
9 = SERVICES  
10 = PUBLIC SERVICES

Constructed dummies:  
DIND1: PIND = 1 (base group)  
DIND2: PIND = 2  
DIND3: PIND = 3.4  
DIND4: PIND = 5  
DIND5: PIND = 6  
DIND6: PIND = 7  
DIND7: PIND = 8  
DIND8: PIND = 9  
DIND9: PIND = 10  
DINDMIS: PIND = 0

286
Appendix 5.B: Effects of Selection Criteria on the Sub-Samples Size

For each country considered in the present study, the full description of the number of observations remaining in the sub-samples after each of the selections illustrated in Section 5.2.3 is the following:

a) United States
   i) male individuals: this selection gives an initial sample of 11,837 observations;
   ii) individuals 15 years old or older: this selection does not eliminate any case and leaves a sample of 11,837 observations (the minimum age of individuals participating in the original survey is 15);
   iii) employees currently employed, excluding unemployed workers, students, ill disabled, and other individuals not in the labour force: this selection reduces the sample to 7,969 observations (about 67% of the initial sample);
   iv) private and public wage and salary employees, excluding self-employed individuals, unpaid workers, and Government employees (who include military personnel, judges, etc.): this selection reduces the sample to 6,303 observations (about 53% of the initial sample, with a reduction of about -21% with respect to the previous sub-sample);
   v) regular full-time or part-time workers, employed for the whole year of reference (52 weeks per year): this selection reduces the sample to 4,426 observations (about 37% of the initial sample, with a reduction of about -30% with respect to the previous sub-sample);
   vi) workers who do not report missing values for the wage variable and/or the hours worked variable: this selection does not eliminate any case and leaves a sample of 4,426 observations;
   vii) workers who report an hourly wage rate greater than 1 US$ and less than or equal to 250 US$: this last selection leads to a final sample size of 4,400 observations (about 37% of the initial sample, with a reduction of about -0.6% with respect to the previous sub-sample).

b) Canada
   i) male individuals: this selection gives an initial sample of 11,977 observations;
   ii) individuals 15 years old or older: this selection does not eliminate any case and leaves a sample of 11,977 observations (the minimum age of individuals participating in the original survey is 15);
employees currently employed, excluding unemployed workers and other individuals not in the labour force: this selection reduces the sample to 7,747 observations (about 65% of the initial sample):

iv) private and public wage and salary employees, excluding self-employed individuals and unpaid family workers: this selection reduces the sample to 6,562 observations (about 55% of the initial sample, with a reduction of about -15% with respect to the previous sub-sample);

v) regular full-time or part-time workers, employed for the whole year of reference (52 weeks per year): this selection reduces the sample to 5,098 observations (about 43% of the initial sample, with a reduction of about -22% with respect to the previous sub-sample):

vi) workers who do not report missing values for the wage variable and/or the hours worked variable: the first selection reduces the sample to 5,054 observations (about 42% of the initial sample, with a reduction of about -0.9% with respect to the previous sub-sample), while the second selection does not eliminate any case and leaves a sample of 5,054 observations;

vii) workers who report an hourly wage rate greater than 1 Can$ and less than or equal to 320 Can$: this last selection leads to a final sample size of 5,000 observations (about 42% of the initial sample, with a reduction of about -1% with respect to the previous sub-sample).

c) Australia

i) male individuals: this selection gives an initial sample of 8,142 observations:

ii) individuals 15 years old or older: this selection does not eliminate any case and leaves a sample of 8,142 observations (the minimum age of individuals participating in the original survey is 15);

iii) employees full-time or part-time employed, excluding permanently disabled individuals, students, unpaid voluntary workers, unemployed workers, and other individuals not in the labour force: this selection reduces the sample to 5,733 observations (about 70% of the initial sample):

iv) private and public wage and salary employees, excluding self-employed individuals, family workers, and military personnel: this selection reduces the sample to 4,353 observations (about 53% of the initial sample, with a reduction of about -24% with respect to the previous sub-sample);
v) regular full-time or part-time workers, employed for the whole year of reference (52 weeks per year): this selection reduces the sample to 3,586 observations (about 44% of the initial sample, with a reduction of about -18% with respect to the previous sub-sample);

vi) workers who do not report missing values for the wage variable and/or the hours worked variable: the first selection reduces the sample to 3,562 observations (about 44% of the initial sample, with a reduction of about -0.7% with respect to the previous sub-sample), while the second selection does not eliminate any case and leaves a sample of 3,562 observations;

vii) workers who report an hourly wage rate greater than 1 Aus$ and less than or equal to 365 Aus$: this last selection leads to a final sample size of 3,543 observations (about 44% of the initial sample, with a reduction of about -0.5% with respect to the previous sub-sample).

d) Germany

i) male individuals: this selection gives an initial sample of 5,573 observations:

ii) individuals 15 years old or older: this selection does not eliminate any case and leaves a sample of 5,573 observations (the minimum age of individuals participating in the original survey is 16);

iii) private and public employees currently employed, excluding individuals not in the labour force, unemployed workers, students, and military personnel: this selection reduces the sample to 3,821 observations (about 69% of the initial sample);

iv) wage and salary employees, excluding professionals, self-employed workers, trainees, and civil servants qualified as Beamten, who being public officials are subject to peculiar regulations affecting their position in the labour market: this selection reduces the sample to 2,853 observations (about 51% of the initial sample, with a reduction of about -25% with respect to the previous sub-sample);

v) regular full-time or part-time workers, employed for the whole year of reference (52 weeks per year): this selection reduces the sample to 2,601 observations (about 47% of the initial sample, with a reduction of about -9% with respect to the previous sub-sample);

vi) workers who do not report missing values for the wage variable and/or the hours worked variable: the first selection reduces the sample to 2,588 observations (about 46% of the initial sample, with a reduction of about -0.5% with respect to the previous sub-sample), and the second selection reduces the sample to 2,452 observations (about 44% of the initial sample, with a reduction of about -5% with respect to the previous sub-sample);
vii) workers who report an hourly wage rate greater than 1 DM and less than or equal to 400 DM: this last selection leads to a final sample size of 2,447 observations (about 44% of the initial sample, with a reduction of about -0.2% with respect to the previous sub-sample).

e) Netherlands

i) male individuals: this selection gives an initial sample of 4,045 observations:

ii) individuals 15 years old or older: this selection does not eliminate any case and leaves a sample of 4,045 observations (the minimum age of individuals participating in the original survey is 18):

iii) employees in the labour force, excluding unemployed workers, students, and other individuals not in the labour force: this selection reduces the sample to 2,585 observations (about 64% of the initial sample):

iv) private and public wage and salary employees, excluding self-employed individuals and unpaid family workers: this selection reduces the sample to 2,210 observations (about 55% of the initial sample, with a reduction of about -15% with respect to the previous sub-sample):

v) regular full-time or part-time workers, who have not received unemployment benefits in the period of reference and, therefore, have been employed for the whole year of reference: this selection reduces the sample to 2,205 observations (about 55% of the initial sample, with a reduction of about -0.2% with respect to the previous sub-sample):

vi) workers who do not report missing values for the wage variable and/or the hours worked variable: the first selection reduces the sample to 2,152 observations (about 53% of the initial sample, with a reduction of about -2% with respect to the previous sub-sample), and the second selection reduces the sample to 2,086 observations (about 52% of the initial sample, with a reduction of about -3% with respect to the previous sub-sample):

vii) workers who report an hourly wage rate greater than 1 FL and less than or equal to 445 FL: this last selection leads to a final sample size of 2,084 observations (about 52% of the initial sample, with a reduction of about -0.1% with respect to the previous sub-sample).
Appendix 5.C: Estimated Wage Equations

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.678**</td>
<td>(0.065)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mining</td>
<td>1.031*</td>
<td>(0.104)</td>
<td>0.01</td>
<td>55</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.766*</td>
<td>(0.067)</td>
<td>0.28</td>
<td>1.218</td>
</tr>
<tr>
<td>Public utilities, community services</td>
<td>0.929*</td>
<td>(0.084)</td>
<td>0.03</td>
<td>127</td>
</tr>
<tr>
<td>Construction</td>
<td>0.614*</td>
<td>(0.074)</td>
<td>0.07</td>
<td>295</td>
</tr>
<tr>
<td>Trade</td>
<td>0.424*</td>
<td>(0.068)</td>
<td>0.25</td>
<td>1.079</td>
</tr>
<tr>
<td>Transport, communications</td>
<td>0.784*</td>
<td>(0.073)</td>
<td>0.08</td>
<td>333</td>
</tr>
<tr>
<td>Finance, insurance, real estate</td>
<td>0.751*</td>
<td>(0.072)</td>
<td>0.09</td>
<td>407</td>
</tr>
<tr>
<td>Personal, social services</td>
<td>0.685*</td>
<td>(0.069)</td>
<td>0.18</td>
<td>801</td>
</tr>
</tbody>
</table>

SE of the regression                      | 0.601              |                |                  |                 |

* Statistically different from 0 at the 5% significance level.

$$ F $$-statistic (8. 4391)                      | 47.292\**          |                |                  |                 |

$$ R^2 $$                                       | 0.078              |                |                  |                 |

Sample size                                    | 4.400              |                |                  |                 |

* Statistically different from 0 at the 5% significance level.

** Statistically different from 0 at the 1% significance level. The $$ F $$ test that all the estimated slope coefficients jointly equal 0 rejects at the 1% level. The 1% critical point is $$ F_{10} (8. 4391) = 2.511. $$
TABLE 5.C2
CANADA 1987

Estimated wage equation without controls for human capital (OLS standard errors in parentheses)
Dependent variable: logarithm of individual hourly wage

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.719**</td>
<td>(0.059)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mining</td>
<td>1.059**</td>
<td>(0.068)</td>
<td>0.06</td>
<td>302</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.853**</td>
<td>(0.062)</td>
<td>0.21</td>
<td>1,067</td>
</tr>
<tr>
<td>Public utilities, community services</td>
<td>0.859**</td>
<td>(0.064)</td>
<td>0.12</td>
<td>598</td>
</tr>
<tr>
<td>Construction</td>
<td>0.748**</td>
<td>(0.068)</td>
<td>0.06</td>
<td>289</td>
</tr>
<tr>
<td>Trade</td>
<td>0.621**</td>
<td>(0.062)</td>
<td>0.19</td>
<td>944</td>
</tr>
<tr>
<td>Transport, communications</td>
<td>0.897**</td>
<td>(0.064)</td>
<td>0.12</td>
<td>618</td>
</tr>
<tr>
<td>Finance, insurance, real estate</td>
<td>0.830**</td>
<td>(0.066)</td>
<td>0.08</td>
<td>387</td>
</tr>
<tr>
<td>Personal, social services</td>
<td>0.828**</td>
<td>(0.063)</td>
<td>0.14</td>
<td>705</td>
</tr>
</tbody>
</table>

SE of the regression 0.563

\( F \)-statistic (8, 4991) 47.482**

\( R^2 \) 0.069

Sample size 5,000

* Statistically different from 0 at the 5% significance level.

** Statistically different from 0 at the 1% significance level. The \( F \) test that all the estimated slope coefficients jointly equal 0 rejects at the 1% level. The 1% critical point is \( F_{0.01}(8, 4991) = 2.511 \).
TABLE 5.C3
AUSTRALIA 1986

Estimated wage equation without controls for human capital (OLS standard errors in parentheses)
Dependent variable: logarithm of individual hourly wage

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.813**</td>
<td>(0.042)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mining</td>
<td>0.776**</td>
<td>(0.060)</td>
<td>0.02</td>
<td>84</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.443**</td>
<td>(0.044)</td>
<td>0.22</td>
<td>790</td>
</tr>
<tr>
<td>Public utilities, community services</td>
<td>0.588**</td>
<td>(0.044)</td>
<td>0.19</td>
<td>680</td>
</tr>
<tr>
<td>Construction</td>
<td>0.419**</td>
<td>(0.050)</td>
<td>0.06</td>
<td>214</td>
</tr>
<tr>
<td>Trade</td>
<td>0.323**</td>
<td>(0.045)</td>
<td>0.16</td>
<td>554</td>
</tr>
<tr>
<td>Transport, communications</td>
<td>0.565**</td>
<td>(0.046)</td>
<td>0.12</td>
<td>426</td>
</tr>
<tr>
<td>Finance, insurance, real estate</td>
<td>0.520**</td>
<td>(0.048)</td>
<td>0.08</td>
<td>286</td>
</tr>
<tr>
<td>Personal, social services</td>
<td>0.564**</td>
<td>(0.046)</td>
<td>0.12</td>
<td>420</td>
</tr>
</tbody>
</table>

SE of the regression                    | 0.395              |                |                  |                 |
$F$-statistic (8, 3534)                  | 46.385**           |                |                  |                 |
$R^2$                                       | 0.093              |                |                  |                 |
Sample size                                 | 3,543              |                |                  |                 |

* Statistically different from 0 at the 5% significance level.
** Statistically different from 0 at the 1% significance level. The $F$ test that all the estimated slope coefficients jointly equal 0 rejects at the 1% level. The 1% critical point is $F_m (8, 3534) = 2.511$. 

293
TABLE 5.C4
GERMANY 1985

Estimated wage equation without controls for human capital (OLS standard errors in parentheses)
Dependent variable: logarithm of individual hourly wage

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.649*</td>
<td>(0.115)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mining</td>
<td>0.281</td>
<td>(0.152)</td>
<td>0.01</td>
<td>28</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.242*</td>
<td>(0.116)</td>
<td>0.50</td>
<td>1233</td>
</tr>
<tr>
<td>Public utilities, community services</td>
<td>0.306*</td>
<td>(0.142)</td>
<td>0.02</td>
<td>40</td>
</tr>
<tr>
<td>Construction</td>
<td>0.147</td>
<td>(0.121)</td>
<td>0.08</td>
<td>206</td>
</tr>
<tr>
<td>Trade</td>
<td>0.018</td>
<td>(0.120)</td>
<td>0.10</td>
<td>252</td>
</tr>
<tr>
<td>Transport, communications</td>
<td>0.205</td>
<td>(0.126)</td>
<td>0.04</td>
<td>106</td>
</tr>
<tr>
<td>Finance, insurance, real estate</td>
<td>0.528**</td>
<td>(0.128)</td>
<td>0.04</td>
<td>89</td>
</tr>
<tr>
<td>Personal, social services</td>
<td>0.247*</td>
<td>(0.120)</td>
<td>0.10</td>
<td>254</td>
</tr>
<tr>
<td>Dummy for missing industry</td>
<td>0.242*</td>
<td>(0.120)</td>
<td>0.09</td>
<td>218</td>
</tr>
</tbody>
</table>

SE of the regression                          | 0.527              |                |                  |                 |
F-statistic (9, 2437)                          | 8.861**            |                |                  |                 |
\( R^2 \)                                      | 0.028              |                |                  |                 |
Sample size                                    | 2.447              |                |                  |                 |

* Statistically different from 0 at the 5% significance level.
** Statistically different from 0 at the 1% significance level. The \( F \) test that all the estimated slope coefficients jointly equal 0 rejects at the 1% level. The 1% critical point is \( F_{0.01}(9, 2437) = 2.407 \).
TABLE 5.C5
NETHERLANDS 1987

Estimated wage equation *without* controls for human capital (OLS standard errors in parentheses)

*Dependent variable*: logarithm of individual hourly wage

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.872**</td>
<td>(0.084)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mining</td>
<td>0.453*</td>
<td>(0.216)</td>
<td>0.00</td>
<td>5</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.189*</td>
<td>(0.087)</td>
<td>0.20</td>
<td>414</td>
</tr>
<tr>
<td>Public utilities, community services</td>
<td>0.212</td>
<td>(0.142)</td>
<td>0.01</td>
<td>15</td>
</tr>
<tr>
<td>Construction</td>
<td>0.091</td>
<td>(0.090)</td>
<td>0.10</td>
<td>198</td>
</tr>
<tr>
<td>Trade</td>
<td>0.135</td>
<td>(0.088)</td>
<td>0.15</td>
<td>315</td>
</tr>
<tr>
<td>Transport, communications</td>
<td>0.124</td>
<td>(0.092)</td>
<td>0.07</td>
<td>145</td>
</tr>
<tr>
<td>Finance, insurance, real estate</td>
<td>0.326**</td>
<td>(0.089)</td>
<td>0.11</td>
<td>237</td>
</tr>
<tr>
<td>Personal, social services</td>
<td>0.301**</td>
<td>(0.086)</td>
<td>0.32</td>
<td>661</td>
</tr>
<tr>
<td>Dummy for missing industry</td>
<td>0.366**</td>
<td>(0.100)</td>
<td>0.03</td>
<td>66</td>
</tr>
</tbody>
</table>

SE of the regression 0.445

F-statistic (9, 2074) 9.731**

$R^2$ 0.036

Sample size 2.084

* Statistically different from 0 at the 5% significance level.
** Statistically different from 0 at the 1% significance level. The $F$ test that all the estimated slope coefficients jointly equal 0 rejects at the 1% level. The 1% critical point is $F_{0.01}(9, 2074) = 2.407.$
### TABLE 5.C6
**UNITED STATES 1986**

Estimated wage equation with controls for human capital (OLS standard errors in parentheses)

*Dependent variable:* logarithm of individual hourly wage

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interceot</td>
<td>0.062</td>
<td>(0.103)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.062**</td>
<td>(0.004)</td>
<td>38.49</td>
<td>4,400</td>
</tr>
<tr>
<td>Age²</td>
<td>-0.0006**</td>
<td>(0.0000)</td>
<td>1,634.32</td>
<td>4,400</td>
</tr>
<tr>
<td>Education variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Completed junior high school</td>
<td>-0.027</td>
<td>(0.066)</td>
<td>0.04</td>
<td>165</td>
</tr>
<tr>
<td>Some high school</td>
<td>0.097</td>
<td>(0.058)</td>
<td>0.10</td>
<td>422</td>
</tr>
<tr>
<td>Completed high school</td>
<td>0.241**</td>
<td>(0.054)</td>
<td>0.37</td>
<td>1,637</td>
</tr>
<tr>
<td>Some college/university</td>
<td>0.361**</td>
<td>(0.056)</td>
<td>0.20</td>
<td>875</td>
</tr>
<tr>
<td>Completed college/university bachelor</td>
<td>0.488**</td>
<td>(0.058)</td>
<td>0.16</td>
<td>692</td>
</tr>
<tr>
<td>Post-graduate studies</td>
<td>0.605**</td>
<td>(0.061)</td>
<td>0.11</td>
<td>506</td>
</tr>
<tr>
<td>Dummy for missing education</td>
<td>-0.178</td>
<td>(0.198)</td>
<td>0.00</td>
<td>7</td>
</tr>
<tr>
<td>Marital status variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>0.184**</td>
<td>(0.023)</td>
<td>0.68</td>
<td>2,984</td>
</tr>
<tr>
<td>Widowed</td>
<td>0.081</td>
<td>(0.100)</td>
<td>0.01</td>
<td>28</td>
</tr>
<tr>
<td>Divorced</td>
<td>0.067</td>
<td>(0.034)</td>
<td>0.08</td>
<td>336</td>
</tr>
<tr>
<td>Separated</td>
<td>0.036</td>
<td>(0.059)</td>
<td>0.02</td>
<td>84</td>
</tr>
<tr>
<td>Skill variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Machine operating blue-collar worker</td>
<td>0.0001</td>
<td>(0.026)</td>
<td>0.14</td>
<td>634</td>
</tr>
<tr>
<td>Precision blue-collar worker</td>
<td>0.103**</td>
<td>(0.037)</td>
<td>0.06</td>
<td>245</td>
</tr>
<tr>
<td>White-collar worker</td>
<td>0.054*</td>
<td>(0.027)</td>
<td>0.13</td>
<td>585</td>
</tr>
<tr>
<td>Technician</td>
<td>0.207**</td>
<td>(0.047)</td>
<td>0.03</td>
<td>136</td>
</tr>
<tr>
<td>Professional</td>
<td>0.203**</td>
<td>(0.031)</td>
<td>0.13</td>
<td>594</td>
</tr>
<tr>
<td>Manager</td>
<td>0.222**</td>
<td>(0.025)</td>
<td>0.21</td>
<td>917</td>
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</table>

(continued)
TABLE 5.C6 (continued)

<table>
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<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mining</td>
<td>0.668''</td>
<td>(0.089)</td>
<td>0.01</td>
<td>55</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.475''</td>
<td>(0.059)</td>
<td>0.28</td>
<td>1.218</td>
</tr>
<tr>
<td>Public utilities, community services</td>
<td>0.610''</td>
<td>(0.072)</td>
<td>0.03</td>
<td>127</td>
</tr>
<tr>
<td>Construction</td>
<td>0.428''</td>
<td>(0.063)</td>
<td>0.07</td>
<td>295</td>
</tr>
<tr>
<td>Trade</td>
<td>0.240''</td>
<td>(0.058)</td>
<td>0.25</td>
<td>1.079</td>
</tr>
<tr>
<td>Transport, communications</td>
<td>0.478''</td>
<td>(0.063)</td>
<td>0.08</td>
<td>333</td>
</tr>
<tr>
<td>Finance, insurance, real estate</td>
<td>0.364''</td>
<td>(0.062)</td>
<td>0.09</td>
<td>407</td>
</tr>
<tr>
<td>Personal, social services</td>
<td>0.239''</td>
<td>(0.060)</td>
<td>0.18</td>
<td>801</td>
</tr>
</tbody>
</table>

SE of the regression                     | 0.506              |
F-statistic (27, 4372)                    | 87.678''           |
R²                                        | 0.347              |
Sample size                               | 4.400              |

* Statistically different from 0 at the 5% significance level.
** Statistically different from 0 at the 1% significance level. The F test that all the estimated slope coefficients jointly equal 0 rejects at the 1% level. The 1% critical point is $F_{0.01}(27, 4372) = 1.739$. 

297
Estimated wage equation with controls for human capital (OLS standard errors in parentheses)

Dependent variable: logarithm of individual hourly wage

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.387**</td>
<td>(0.093)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.058**</td>
<td>(0.004)</td>
<td>38.19</td>
<td>5,000</td>
</tr>
<tr>
<td>Age$^2$</td>
<td>-0.006**</td>
<td>(0.0001)</td>
<td>1.592.58</td>
<td>5,000</td>
</tr>
<tr>
<td>Education variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Some secondary school</td>
<td>0.021</td>
<td>(0.030)</td>
<td>0.10</td>
<td>502</td>
</tr>
<tr>
<td>Completed secondary (short) or vocational school</td>
<td>0.084**</td>
<td>(0.025)</td>
<td>0.23</td>
<td>1,151</td>
</tr>
<tr>
<td>Completed university-oriented high school</td>
<td>0.138*</td>
<td>(0.056)</td>
<td>0.02</td>
<td>92</td>
</tr>
<tr>
<td>Some college diploma</td>
<td>0.160**</td>
<td>(0.031)</td>
<td>0.09</td>
<td>467</td>
</tr>
<tr>
<td>Completed college diploma</td>
<td>0.162**</td>
<td>(0.027)</td>
<td>0.16</td>
<td>780</td>
</tr>
<tr>
<td>University degree</td>
<td>0.352**</td>
<td>(0.030)</td>
<td>0.16</td>
<td>804</td>
</tr>
<tr>
<td>Dummy for missing education</td>
<td>-0.119**</td>
<td>(0.030)</td>
<td>0.11</td>
<td>526</td>
</tr>
<tr>
<td>Marital status variables:</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>0.203**</td>
<td>(0.022)</td>
<td>0.74</td>
<td>3,683</td>
</tr>
<tr>
<td>Other marital status</td>
<td>0.197**</td>
<td>(0.036)</td>
<td>0.06</td>
<td>292</td>
</tr>
<tr>
<td>Skill variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Machine operating blue-collar worker</td>
<td>-0.001</td>
<td>(0.022)</td>
<td>0.22</td>
<td>1,078</td>
</tr>
<tr>
<td>White-collar worker</td>
<td>-0.061**</td>
<td>(0.024)</td>
<td>0.23</td>
<td>1,143</td>
</tr>
<tr>
<td>Professional</td>
<td>0.077*</td>
<td>(0.031)</td>
<td>0.13</td>
<td>673</td>
</tr>
<tr>
<td>Manager</td>
<td>0.072**</td>
<td>(0.025)</td>
<td>0.18</td>
<td>888</td>
</tr>
<tr>
<td>Variables</td>
<td>Parameter estimate</td>
<td>Standard error</td>
<td>Mean of variable</td>
<td>Number of cases</td>
</tr>
<tr>
<td>-----------------------------------------</td>
<td>--------------------</td>
<td>----------------</td>
<td>------------------</td>
<td>-----------------</td>
</tr>
<tr>
<td><strong>Industry variables:</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mining</td>
<td>0.812**</td>
<td>(0.062)</td>
<td>0.06</td>
<td>302</td>
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<tr>
<td>Manufacturing</td>
<td>0.676**</td>
<td>(0.056)</td>
<td>0.21</td>
<td>1,067</td>
</tr>
<tr>
<td>Public utilities, community services</td>
<td>0.467**</td>
<td>(0.060)</td>
<td>0.12</td>
<td>598</td>
</tr>
<tr>
<td>Construction</td>
<td>0.567**</td>
<td>(0.061)</td>
<td>0.06</td>
<td>289</td>
</tr>
<tr>
<td>Trade</td>
<td>0.494**</td>
<td>(0.057)</td>
<td>0.19</td>
<td>944</td>
</tr>
<tr>
<td>Transport, communications</td>
<td>0.657**</td>
<td>(0.058)</td>
<td>0.12</td>
<td>618</td>
</tr>
<tr>
<td>Finance, insurance, real estate</td>
<td>0.536**</td>
<td>(0.062)</td>
<td>0.08</td>
<td>387</td>
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<tr>
<td>Personal, social services</td>
<td>0.569**</td>
<td>(0.059)</td>
<td>0.14</td>
<td>705</td>
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<tr>
<td>SE of the regression</td>
<td>0.502</td>
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<tr>
<td><em>F</em>-statistic (23, 4976)</td>
<td>77.800**</td>
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<tr>
<td>$\bar{R}^2$</td>
<td>0.261</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Sample size</td>
<td>5,000</td>
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<td></td>
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</tbody>
</table>

* Statistically different from 0 at the 5% significance level.

** Statistically different from 0 at the 1% significance level. The *F* test that all the estimated slope coefficients jointly equal 0 rejects at the 1% level. The 1% critical point is $F_{0.01} (23, 4976) = 1.810$. 

299
TABLE 5.C8
AUSTRALIA 1986

Estimated wage equation with controls for human capital (OLS standard errors in parentheses)

*Dependent variable*: logarithm of individual hourly wage

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.492**</td>
<td>(0.070)</td>
<td></td>
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</tr>
<tr>
<td>Age</td>
<td>0.059**</td>
<td>(0.003)</td>
<td>37.17</td>
<td>3,543</td>
</tr>
<tr>
<td>Age^2</td>
<td>-0.0006**</td>
<td>(0.0000)</td>
<td>1.520.61</td>
<td>3,543</td>
</tr>
<tr>
<td>Education variables:</td>
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<td></td>
</tr>
<tr>
<td>Completed secondary school</td>
<td>0.093**</td>
<td>(0.019)</td>
<td>0.13</td>
<td>450</td>
</tr>
<tr>
<td>Trade certificate</td>
<td>0.069**</td>
<td>(0.015)</td>
<td>0.26</td>
<td>936</td>
</tr>
<tr>
<td>Other certificate</td>
<td>0.152**</td>
<td>(0.021)</td>
<td>0.13</td>
<td>457</td>
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<tr>
<td>Bachelor degree or higher</td>
<td>0.246**</td>
<td>(0.023)</td>
<td>0.12</td>
<td>426</td>
</tr>
<tr>
<td>Dummy for missing education</td>
<td>-0.355</td>
<td>(0.236)</td>
<td>0.00</td>
<td>2</td>
</tr>
<tr>
<td>Marital status variables:</td>
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<td></td>
</tr>
<tr>
<td>Married</td>
<td>0.067**</td>
<td>(0.017)</td>
<td>0.68</td>
<td>2,398</td>
</tr>
<tr>
<td>Separated/widowed/divorced</td>
<td>0.061*</td>
<td>(0.028)</td>
<td>0.06</td>
<td>215</td>
</tr>
<tr>
<td>Skill variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Machine operating blue-collar worker</td>
<td>0.066**</td>
<td>(0.022)</td>
<td>0.13</td>
<td>446</td>
</tr>
<tr>
<td>White-collar worker</td>
<td>0.043*</td>
<td>(0.018)</td>
<td>0.41</td>
<td>1,436</td>
</tr>
<tr>
<td>Professional</td>
<td>0.178**</td>
<td>(0.023)</td>
<td>0.22</td>
<td>794</td>
</tr>
<tr>
<td>Manager</td>
<td>0.207**</td>
<td>(0.025)</td>
<td>0.10</td>
<td>346</td>
</tr>
</tbody>
</table>

(continued)
<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mining</td>
<td>0.656**</td>
<td>(0.051)</td>
<td>0.02</td>
<td>84</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.379**</td>
<td>(0.038)</td>
<td>0.22</td>
<td>790</td>
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<td>Public utilities, community services</td>
<td>0.367**</td>
<td>(0.039)</td>
<td>0.19</td>
<td>680</td>
</tr>
<tr>
<td>Construction</td>
<td>0.373**</td>
<td>(0.043)</td>
<td>0.06</td>
<td>214</td>
</tr>
<tr>
<td>Trade</td>
<td>0.291**</td>
<td>(0.039)</td>
<td>0.16</td>
<td>554</td>
</tr>
<tr>
<td>Transport, communications</td>
<td>0.455**</td>
<td>(0.040)</td>
<td>0.12</td>
<td>426</td>
</tr>
<tr>
<td>Finance, insurance, real estate</td>
<td>0.377**</td>
<td>(0.041)</td>
<td>0.08</td>
<td>286</td>
</tr>
<tr>
<td>Personal, social services</td>
<td>0.400**</td>
<td>(0.040)</td>
<td>0.12</td>
<td>420</td>
</tr>
<tr>
<td>SE of the regression</td>
<td>0.333</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>F-statistic (21, 3521)</td>
<td>94.090**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.356</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample size</td>
<td>3.543</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Statistically different from 0 at the 5% significance level.
** Statistically different from 0 at the 1% significance level. The $F$ test that all the estimated slope coefficients jointly equal 0 rejects at the 1% level. The 1% critical point is $F_{0.01}(21, 3521) = 1.854$. 
TABLE 5.C9

GERMANY 1985

Estimated wage equation with controls for human capital (OLS standard errors in parentheses)
Dependent variable: logarithm of individual hourly wage

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.163**</td>
<td>(0.164)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.062**</td>
<td>(0.007)</td>
<td>40.42</td>
<td>2,447</td>
</tr>
<tr>
<td>Age²</td>
<td>-0.0007**</td>
<td>(0.0001)</td>
<td>1.754.41</td>
<td>2,447</td>
</tr>
</tbody>
</table>

Education variables:

| Vocational school                | 0.003              | (0.034)        | 0.12             | 301            |
| Technical high school            | 0.174**            | (0.056)        | 0.04             | 87             |
| General high school              | 0.123*             | (0.051)        | 0.05             | 129            |
| Other education                  | 0.046              | (0.048)        | 0.04             | 104            |
| Dummy for missing education      | -0.007             | (0.034)        | 0.10             | 253            |

Marital status variables:

| Married                          | 0.100**            | (0.032)        | 0.76             | 1,865          |
| Separated                        | 0.051              | (0.061)        | 0.03             | 83             |
| Widowed                          | 0.337**            | (0.098)        | 0.01             | 26             |
| Divorced                         | 0.142*             | (0.067)        | 0.02             | 61             |

Skill variables:

| Semi-skilled worker              | 0.050              | (0.042)        | 0.22             | 548            |
| Skilled worker/craftsman         | 0.145**            | (0.041)        | 0.31             | 757            |
| Foreman                          | 0.217**            | (0.060)        | 0.04             | 104            |
| Building foreman                 | 0.356**            | (0.088)        | 0.01             | 36             |
| White-collar foreman             | 0.394**            | (0.076)        | 0.02             | 53             |
| White-collar worker              | 0.056              | (0.068)        | 0.03             | 73             |
| Qualified white-collar worker    | 0.323**            | (0.048)        | 0.15             | 374            |
| High-qualified white-collar worker | 0.483**           | (0.054)        | 0.12             | 288            |
| White-collar manager             | 0.690**            | (0.086)        | 0.02             | 43             |

(continued)
### TABLE 5.0 (continued)

<table>
<thead>
<tr>
<th>Industry variables:</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mining</td>
<td>0.185</td>
<td>(0.136)</td>
<td>0.01</td>
<td>28</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.112</td>
<td>(0.104)</td>
<td>0.50</td>
<td>1,233</td>
</tr>
<tr>
<td>Public utilities, community services</td>
<td>0.124</td>
<td>(0.127)</td>
<td>0.02</td>
<td>40</td>
</tr>
<tr>
<td>Construction</td>
<td>0.004</td>
<td>(0.108)</td>
<td>0.08</td>
<td>206</td>
</tr>
<tr>
<td>Trade</td>
<td>-0.063</td>
<td>(0.107)</td>
<td>0.10</td>
<td>252</td>
</tr>
<tr>
<td>Transport, communications</td>
<td>0.073</td>
<td>(0.113)</td>
<td>0.04</td>
<td>106</td>
</tr>
<tr>
<td>Finance, insurance, real estate</td>
<td>0.165</td>
<td>(0.116)</td>
<td>0.04</td>
<td>89</td>
</tr>
<tr>
<td>Personal, social services</td>
<td>-0.005</td>
<td>(0.108)</td>
<td>0.10</td>
<td>254</td>
</tr>
<tr>
<td>Dummy for missing industry</td>
<td>0.088</td>
<td>(0.108)</td>
<td>0.09</td>
<td>218</td>
</tr>
</tbody>
</table>

SE of the regression | 0.469

*Statistically different from 0 at the 5% significance level.

**Statistically different from 0 at the 1% significance level. The \( F \) test that all the estimated slope coefficients jointly equal 0 rejects at the 1% level. The 1% critical point is \( F_{0.01}(29, 2417) = 1.710 \).
TABLE 5.C10

NETHERLANDS 1987

Estimated wage equation with controls for human capital (OLS standard errors in parentheses)
Dependent variable: logarithm of individual hourly wage

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.978**</td>
<td>(0.126)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.078**</td>
<td>(0.006)</td>
<td>37.11</td>
<td>2,084</td>
</tr>
<tr>
<td>Age²</td>
<td>-0.0008**</td>
<td>(0.0001)</td>
<td>1.47637</td>
<td>2,084</td>
</tr>
</tbody>
</table>

Education variables:

- Extended primary school    0.214**  (0.023)  0.26  544
- Secondary school           0.287**  (0.028)  0.16  339
- University                 0.493**  (0.031)  0.10  214
- Dummy for missing education 0.049*   (0.024)  0.18  366

Marital status variables:

- Married                   0.103**  (0.023)  0.76  1,574
- Widowed                   -0.050   (0.149)  0.00  6
- Divorced/separated        0.086    (0.051)  0.03  61

Skill variables:

- Intermediate              0.037    (0.021)  0.24  501
- Higher                    0.157**  (0.024)  0.20  416

(continued)
TABLE 5.C10 (continued)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>Mean of variable</th>
<th>Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mining</td>
<td>0.293</td>
<td>(0.173)</td>
<td>0.00</td>
<td>5</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.128</td>
<td>(0.070)</td>
<td>0.20</td>
<td>414</td>
</tr>
<tr>
<td>Public utilities, community services</td>
<td>0.011</td>
<td>(0.114)</td>
<td>0.01</td>
<td>15</td>
</tr>
<tr>
<td>Construction</td>
<td>0.110</td>
<td>(0.072)</td>
<td>0.10</td>
<td>198</td>
</tr>
<tr>
<td>Trade</td>
<td>0.105</td>
<td>(0.070)</td>
<td>0.15</td>
<td>315</td>
</tr>
<tr>
<td>Transport, communications</td>
<td>0.069</td>
<td>(0.074)</td>
<td>0.07</td>
<td>145</td>
</tr>
<tr>
<td>Finance, insurance, real estate</td>
<td>0.137</td>
<td>(0.072)</td>
<td>0.11</td>
<td>237</td>
</tr>
<tr>
<td>Personal, social services</td>
<td>0.053</td>
<td>(0.069)</td>
<td>0.32</td>
<td>661</td>
</tr>
<tr>
<td>Dummy for missing industry</td>
<td>0.194*</td>
<td>(0.081)</td>
<td>0.03</td>
<td>66</td>
</tr>
</tbody>
</table>

SE of the regression 0.355

$F$-statistic (20, 2063) 67.203**

$R^2$ 0.389

Sample size 2.084

* Statistically different from 0 at the 5% significance level.

** Statistically different from 0 at the 1% significance level. The $F$ test that all the estimated slope coefficients jointly equal 0 rejects at the 1% level. The 1% critical point is $F_{n1} (20, 2063) = 1.878$. 
Appendix 5.D: Comparisons between Evidence from LIS Data and Evidence from Other Sources: The United States, Australia, and Germany

In this Appendix I present a comparison between the inter-industry wage differentials estimated with LIS data - described in Section 5.3 - and those estimated by other authors with different data sources for a selection of countries: the United States, Australia, and Germany. Due to the limited amount of variables available in the LIS data-sets and to the indirect nature of the access to the data, the analysis in the present Chapter is less accurate than the ones proposed in other studies of the inter-industry wage structure. Therefore, I want to try and evaluate to what extent the results presented in this Chapter are affected by this limited accuracy. Evidence based on an alternative data source for the United States is available from Krueger and Summers (1988) and for Australia can be found in Borland and Suen (1990). In the case of Germany, I can exploit the results derived directly from the SOEP data and previously presented in Chapter 4. Given the purpose of the comparisons, I will limit my attention to wage differentials estimated with controls for human capital and socio-demographic characteristics in the wage regression.

a) United States

The analysis proposed by Krueger and Summers (1988) and that based on LIS data differ in several aspects. Data are derived from the same source, the Current Population Survey (CPS), but refer to different years, 1984 and 1986 respectively. Differently from the sample selected from LIS data, the sub-sample of interest includes, in Krueger and Summers's case, male and female private workers in non-agricultural sectors. Full-year employment in the reference year is not controlled for. The treatment of missing values is not specified. Their various selections lead to a final sample of 11,512 individuals. Krueger and Summers's dependent hourly wage variable is defined as usual weekly earnings divided by usual weekly hours of work, which represents a measure of the hourly wage rate identical to the hourly wage used in my LIS analysis. The list of controls for human capital, socio-demographic.

---

61 The original CPS variables for earnings and hours worked are annual gross wage or salary in the reference year and usual hours worked per week in the reference year, respectively. It is therefore likely - unfortunately, exact information is not provided - that Krueger and Summers calculate their hourly wage as

\[
\text{"usual weekly earnings"} = \frac{\text{annual gross wage or salary}}{\text{usual weekly hours of work}} \times \frac{52}{\text{usual hours worked per week}}.
\]
and working conditions employed by Krueger and Summers is much richer. It includes education, age, occupation, region, sex, race, central city, union membership, marital status, veteran status dummies, and a number of interaction terms. Education is defined in terms of years of schooling and age is represented by a set of six dummy variables. For reasons of comparability, I consider here the estimates Krueger and Summers provide for one-digit industries, which implies the inclusion of 7 industry dummies in the wage regression. The method of estimation of the wage regression is OLS in both studies.

The estimates of industry differentials in deviation form obtained with LIS data and by Krueger and Summers are summarized in Table 5.D1. Discrepancies in the classifications of production activities and in the sub-samples considered limit the comparable sectors to the 7 cases appearing in the Table. In spite of the several differences underlying the two studies, the results from the two regression analyses seem quite similar in terms of size, significance and overall variability of wage differentials. The fact of considering a larger set of controls for human capital and working conditions in Krueger and Summers's analysis has - as expected - the effect of reducing, to a certain extent, the size and variability of estimated differentials with respect to the LIS study. The average differential in absolute size decreases from 0.123 to 0.116 (-6%) and the weighted adjusted standard deviation of wage differentials falls from 0.135 to 0.102 (-24%). However, the impact of a larger set of controls on the overall structure of industry differentials seems rather limited. The values appearing in the two columns of Table 5.D1 are plotted in Figure 5.D1, which shows the existence of a strong positive linear relationship between the two inter-industry wage structures. The Pearson and Spearman correlations between the vectors of differentials are, respectively, 0.961 (one-sided p-value 0.000) and 0.929 (one-sided p-value 0.005).

b) Australia

The analysis of the Australian inter-industry wage structure by Borland and Suen (1990) and that presented in this Chapter use exactly the same data source, the 1986 Australian Income Distribution Survey. The two studies, however, present several differences thus obtaining a measure of the hourly wage which is identical to the one defined with LIS data (see Sub-Section 5.2.4)

\[
\text{annual gross wage or salary} = \frac{\text{annual gross wage or salary}}{52 \times \text{(usual hours worked per week)}}
\]
### TABLE 5.D1
UNITED STATES

Estimated wage differentials with controls for human capital: deviations from the employment-weighted mean differential (standard errors in parentheses)

<table>
<thead>
<tr>
<th>Sectors</th>
<th>LIS data 1986</th>
<th>Standard errors(^a)</th>
<th>Knueger &amp; Summers(^b) 1984</th>
<th>Standard errors(^c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2. Mining</td>
<td>0.309(^*)</td>
<td>(0.068)</td>
<td>0.222(^*)</td>
<td>(0.075)</td>
</tr>
<tr>
<td>3. Manufacturing</td>
<td>0.117(^*)</td>
<td>(0.013)</td>
<td>0.091(^*)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>5. Construction</td>
<td>0.070(^*)</td>
<td>(0.029)</td>
<td>0.108(^*)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>6. Trade</td>
<td>-0.118(^*)</td>
<td>(0.014)</td>
<td>-0.111(^*)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>7. Transport. communications</td>
<td>0.119(^*)</td>
<td>(0.027)</td>
<td>0.145(^*)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>8. Finance, insurance. real estate</td>
<td>0.006</td>
<td>(0.024)</td>
<td>0.055</td>
<td>(0.034)</td>
</tr>
<tr>
<td>9. Personal, social services</td>
<td>-0.119(^*)</td>
<td>(0.018)</td>
<td>-0.078(^*)</td>
<td>(0.032)</td>
</tr>
</tbody>
</table>

Average differential in absolute size: 0.123
Weighted adjusted standard deviation of wage differentials: 0.135
\(\bar{R}^2\): 0.347
Sample size: 4,400

\(^a\) Standard errors of the differentials in deviation form.
\(^b\) Source: Krueger and Summers (1988, Table 1).
\(^c\) Unadjusted OLS standard errors.
\(^*\) Statistically different from 0 at the 5% significance level.
\(^\ast\) Statistically different from 0 at the 1% significance level.

### FIGURE 5.D1
UNITED STATES

Estimated wage differentials with controls for human capital

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308
in the selected sub-samples and in the variables entering the wage regression. The sub-sample considered by Borland and Suen consists of male employees working full-time exclusively. Workers receiving a hourly wage greater than 250 Aus$ are considered to be outliers and eliminated from the sample. Full-year employment in the reference year is not controlled for. The treatment of missing values is not specified. Their final sample contains 4,574 observations. Borland and Suen's dependent hourly wage variable is constructed as (current) usual weekly earnings from wages and salaries divided by usual weekly hours of work, which provides a measure of the hourly wage rate not exactly comparable to the hourly wage used in my LIS analysis\(^{62}\). The set of control variables Borland and Suen include in the wage regression consists of education, experience and its square, state of residence, occupation, country of birth, marital status, participation in a super-annuation scheme, and an education\(\times\)experience interaction. Education is originally expressed as completed qualifications, but transformed by Borland and Suen into years of schooling. Industry dummies are defined through a one-digit classification of production activities into 12 sectors. The estimation technique for the wage regression model is OLS in both studies.

Table 5.D2 reports the industry wage differentials in deviation form estimated with LIS data and by Borland and Suen. Differences in industry classifications may affect the degree of comparability of some sectors in particular, such as public utilities and community services, transport and communications, personal and social services. The inclusion of a richer set of human capital controls in Borland and Suen's wage regression has a rather ambiguous effect on the size and variability of estimated differentials. With respect to the LIS analysis,

\(^{62}\) The 1986 Australian Income Distribution Survey defines two variables for both earnings and hours worked: for earnings, annual gross wage or salary (during the 1985-86 financial year) and current gross wage or salary (at the time of interview, Sept.-Dec. 1986, most recent payment); for hours worked, average hours worked per week (during the 1985-86 financial year) and current hours worked per week (at the time of interview, Sept.-Dec. 1986, most recent amount). Borland and Suen calculate their hourly wage as

\[
\frac{\text{(current) usual weekly earnings from wages and salaries}}{\text{(current) usual weekly hours of work}} = \frac{\text{current gross weekly wage or salary}}{\text{current hours worked per week}}
\]

The LIS data-set for Australia, however, retains only one of the two variables, namely annual gross wage or salary (during the 1985-86 financial year) and current hours worked per week (at the time of interview). The two types of variable, therefore, are not totally compatible, as they refer to different time periods. Also, they produce a measure of the hourly wage which is somewhat different from Borland and Suen's (see Sub-Section 5.2.4)

\[
\frac{\text{annual gross wage or salary}}{52 \times \text{(current hours worked per week)}}
\]

Moreover, as already mentioned in Sub-Section 5.2.4, the LIS weekly hours worked variable is represented by the mid-points of the 9 class intervals originally defined by the survey. Borland and Suen, instead, consider only the first 7 of such intervals and set an upper interval of "hours \(\geq 40\)" (mid-point 45).
**TABLE 5.D2**

**AUSTRALIA**

Estimated wage differentials with controls for human capital: deviations from the employment-weighted mean differential (standard errors in parentheses)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Agriculture</td>
<td>-0.371**</td>
<td>(0.036)</td>
<td>-0.304**</td>
<td>(0.054)</td>
</tr>
<tr>
<td>2. Mining</td>
<td>0.285**</td>
<td>(0.036)</td>
<td>0.344**</td>
<td>(0.032)</td>
</tr>
<tr>
<td>3. Manufacturing</td>
<td>0.008</td>
<td>(0.011)</td>
<td>0.031**</td>
<td>(0.008)</td>
</tr>
<tr>
<td>4. Public utilities, community services</td>
<td>-0.004</td>
<td>(0.013)</td>
<td>0.143**</td>
<td>(0.024)</td>
</tr>
<tr>
<td>5. Construction</td>
<td>0.002</td>
<td>(0.022)</td>
<td>0.037**</td>
<td>(0.010)</td>
</tr>
<tr>
<td>6. Trade</td>
<td>-0.080**</td>
<td>(0.013)</td>
<td>-0.048</td>
<td>(0.045)</td>
</tr>
<tr>
<td>7. Transport, communications</td>
<td>0.084**</td>
<td>(0.015)</td>
<td>0.076**</td>
<td>(0.019)</td>
</tr>
<tr>
<td>8. Finance, insurance, real estate</td>
<td>0.005</td>
<td>(0.019)</td>
<td>0.033**</td>
<td>(0.009)</td>
</tr>
<tr>
<td>9. Personal, social services</td>
<td>0.029</td>
<td>(0.015)</td>
<td>0.062**</td>
<td>(0.014)</td>
</tr>
</tbody>
</table>

Average differential in absolute size: 0.096
Weighted adjusted standard deviation of wage differentials: 0.159

\[ R^2 \] = 0.356

Sample size: 3,543

---

*a* Standard errors of the differentials in deviation form.

*b* Source: Borland and Suen (1990, Table 1).

*c* Unadjusted OLS standard errors.

d Statistically different from 0 at the 5% significance level.

**FIGURE 5.D2**

**AUSTRALIA**

Estimated wage differentials with controls for human capital
the average differential in absolute size increases - contrary to what expected - from 0.096 to 0.120 (+25\%), while the weighted adjusted standard deviation of wage differentials decreases - as expected - but by a very small amount, from 0.159 to 0.158 (-1\%). The global impact of a larger set of controls on the general structure of industry differentials is also mixed. The values contained in the two columns of Table 5.D2 are plotted in Figure 5.D2. The graph suggests the existence of a certain positive relationship between estimated wage structures, as confirmed by the value of the Pearson correlation coefficient which is 0.968 (one-sided p-value 0.000). This result, however, is not confirmed by the Spearman rank correlation, whose value 0.683 (one-sided p-value of 0.05) is instead rather low and not significantly different from zero at the 1% level.

We might be tempted to conclude that here human capital controls have some sizable impact on the structure of industry differentials - at least a larger impact than in the case of the United States - although not always in the direction we might have expected. However, it is worth recalling that the several dissimilarities underlying the two regression analyses, and especially the differences in the definition of the respective dependent hourly wage variables, may considerably affect the overall validity of the comparison between the two sets of results.

c) Germany

The LIS data-set utilized in the present Chapter and the study presented in Chapter 4 rely on the same data source, the Socio-Economic Panel (SOEP), but the LIS data represent a selection of the variables contained in Wave 2 (1985) of the panel, while in Chapter 4 I used the whole Wave 1 (1984) data. The criteria adopted to select the sub-samples of interest are very similar. The major differences are represented by the exclusion of workers who experienced unemployment spells during the reference year in the case of the LIS data and by the restriction to straight-time employees in the case of the SOEP data. This leads to a sample of 2,072 employees selected from the SOEP data-set. Both conditions are required for the construction of the hourly wage dependent variable, which in Chapter 4 is defined as gross earnings in the month preceding the interview divided by four times the normal hours worked weekly. This definition produces a measure of the hourly wage rate which is quite
different from the hourly wage used in the LIS analysis\textsuperscript{61}. The treatment of missing values is analogous in both studies. When I have direct access to the SOEP data, I can define a larger number of controls for human capital, socio-demographic characteristics, and working conditions: age and its square, tenure in the current job and its square, dummies for German and foreign education, skill levels, marital status, number of nights spent in hospital in the previous year, degree of satisfaction with the current job, and size of the firm of employment. A set of 25 dummies is used to classify industry affiliation. In Chapter 4 a Heckman’s sample selection model was estimated to correct for potential selection bias, while in this Chapter the simple OLS method is used to provide estimates for the wage regression.

The results for industry differentials estimated with LIS and SOEP data are given in Table 5.D3. The original 26 SOEP differentials are aggregated by (sample) employment-weighted averages into 8 sectors. Both discrepancies in the classifications of industries and the aggregation procedure may reduce the degree of comparability between the sectors appearing in the Table. In particular, the construction and the finance, insurance, real estate sectors seem to be affected by the differences underlying the two studies. The different results for these two sectors may be due to a lack of controls for labour quality in the case of the LIS study, since labour quality is certainly relatively high in the FIRE sector and relatively low in the construction sector. The use of a larger set of controls for human capital and working conditions in the SOEP analysis has - as expected - the effect of reducing the size of estimated differentials. Compared with the LIS results, the majority of wage differentials become smaller in absolute size and the average differential in absolute size decreases from 0.075 to 0.062 (-17\%). The variability of estimated differentials, instead, seems to increase - contrary to what expected - as the standard deviation of wage differentials rises from 0.061

\textsuperscript{61} The SOEP originally defines two variables for both earnings and hours worked: for earnings, actual gross wage or salary in the month preceding the interview and average gross wage or salary per month in the previous year; for hours worked, actual hours worked per week on average in the month preceding the interview and normal (scheduled) hours worked per week. In Chapter 4 (see Section 4.3) I calculate the hourly wage as

\[ \frac{\text{"gross earnings in the last month"}}{4 \times (\text{"normal hours worked weekly"})} = \frac{\text{actual gross wage or salary in the last month}}{4 \times (\text{normal hours worked per week})}. \]

The LIS data-set for Germany, however, provides only one type of variable, namely annual gross wage or salary in the previous year (which is obtained by the LIS administrators by multiplying by 12 the original average gross wage or salary per month in the previous year) and actual hours worked per week on average in the last month. These two variables, therefore, produce a measure of the hourly wage which is quite different from the one used in Chapter 4 (see Sub-Section 5.2.4)

\[ \frac{12 \times (\text{average gross wage or salary per month in the previous year})}{52 \times (\text{actual hours worked per week on average in the last month})} \]
### TABLE 5.D3

**GERMANY**

Estimated wage differentials with controls for human capital: deviations from the employment-weighted mean differential (standard errors in parentheses).

<table>
<thead>
<tr>
<th>Sectors</th>
<th>LIS data 1985</th>
<th>Standard errors&lt;sup&gt;a&lt;/sup&gt;</th>
<th>SOEP data 1984&lt;sup&gt;c&lt;/sup&gt;</th>
<th>Standard errors&lt;sup&gt;c&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Agriculture</td>
<td>-0.069</td>
<td>(0.102)</td>
<td>-0.100</td>
<td>n.a.</td>
</tr>
<tr>
<td>2. Mining</td>
<td>0.116</td>
<td>(0.089)</td>
<td>0.113</td>
<td>(0.060)</td>
</tr>
<tr>
<td>3. Manufacturing</td>
<td>0.043&lt;sup&gt;b&lt;/sup&gt;</td>
<td>(0.009)</td>
<td>0.032</td>
<td>n.a.</td>
</tr>
<tr>
<td>5. Construction</td>
<td>-0.066&lt;sup&gt;c&lt;/sup&gt;</td>
<td>(0.032)</td>
<td>0.044</td>
<td>(0.053)</td>
</tr>
<tr>
<td>6. Trade</td>
<td>-0.133&lt;sup&gt;b&lt;/sup&gt;</td>
<td>(0.029)</td>
<td>-0.097</td>
<td>n.a.</td>
</tr>
<tr>
<td>7. Transport, communications</td>
<td>0.003</td>
<td>(0.045)</td>
<td>-0.019</td>
<td>n.a.</td>
</tr>
<tr>
<td>8. Finance, insurance, real estate</td>
<td>0.096</td>
<td>(0.051)</td>
<td>-0.004</td>
<td>n.a.</td>
</tr>
<tr>
<td>9. Personal, social services</td>
<td>-0.074&lt;sup&gt;c&lt;/sup&gt;</td>
<td>(0.029)</td>
<td>-0.077</td>
<td>n.a.</td>
</tr>
<tr>
<td>Average differential in absolute size</td>
<td>0.075</td>
<td></td>
<td>0.062</td>
<td></td>
</tr>
<tr>
<td>Weighted adjusted standard deviation of wage differentials</td>
<td>0.061</td>
<td></td>
<td>0.072&lt;sup&gt;d&lt;/sup&gt;</td>
<td></td>
</tr>
<tr>
<td>R&lt;sup&gt;2&lt;/sup&gt;</td>
<td>0.230</td>
<td></td>
<td>n.a.</td>
<td></td>
</tr>
<tr>
<td>Sample size</td>
<td>2.447</td>
<td></td>
<td>2.072</td>
<td></td>
</tr>
</tbody>
</table>

<sup>a</sup> Standard errors of the differentials in deviation form.

<sup>b</sup> Source: Chapter 4 (employment-weighted aggregations of results in Table 4.1).

<sup>c</sup> Unadjusted OLS standard errors.

<sup>d</sup> Unadjusted standard deviation of wage differentials.

Statistically different from 0 at the 5% significance level.

Statistically different from 0 at the 1% significance level.

### FIGURE 5.D3

**GERMANY**

Estimated wage differentials with controls for human capital.
to 0.072 (+18%). This last outcome, however, is not totally reliable. In the case of the LIS results, the reported standard deviation is adjusted by the average standard error of the estimated differentials (see equation (5.2) in Section 5.3), while in the case of the SOEP results, the reported value is the unadjusted standard deviation. This lack of adjustment is likely to imply a considerable upward bias in the estimate of the SOEP standard deviation of wage differentials. The overall impact of a larger set of controls on the structure of industry differentials seems substantial. The values appearing in Table 5.D3 are plotted in Figure 5.D3, which displays a rather weak relationship between wage structures, especially due to the construction and the FIRE sectors. The Pearson and Spearman correlations between the two vectors of differentials are both quite low, 0.747 (one-sided p-value 0.017) and 0.762 (one-sided p-value 0.025) respectively, and not significantly different from zero at the 1% level.

Unlike the case of Australia, here results seem generally unambiguous. Human capital controls have a significant impact on the structure of industry differentials - certainly a larger impact than in the case of the United States - and in the expected direction. However, again, the several dissimilarities underlying the two regression analyses, and in particular the considerable differences in the definition of the dependent hourly wage variables, may substantially affect the validity of the comparison and some caution should be used in the evaluation of these findings.

---

64 The adjustment factor cannot be computed in the case of the SOEP results, due to the non-availability of the standard errors of differentials. The reported differentials, in fact, are not directly estimated, but calculated as employment-weighted averages of the original SOEP estimates.
Appendix 5.E: Minimum Distance Estimation

Minimum distance estimation is a general method to estimate parameters of linear simultaneous-equations models characterized by an unknown structure of the error process (Hsiao, 1986, §3.8). The formulation avoids imposing a priori restrictions on the variance-covariance matrix of the error term, so that serial correlation and heteroscedasticity in the error process can be incorporated.

Consider a linear regression model with an unknown parameter vector \( \Theta = (\theta_1, \ldots, \theta_p)' \) of dimensions \((p \times 1)\). Suppose that there is no direct way to estimate \( \Theta \), but that we know a consistent estimator \( \hat{\pi} \) of a parameter vector \( \pi \) of dimensions \((q \times 1)\) - with \( q \geq p \) - which is related to \( \Theta \) by a set of restrictions, assumed for simplicity to be linear (the generalization for the case of non-linear restrictions can be found in Hsiao, 1986, §3.8):

\[
\pi = R\Theta \tag{5.E1}
\]

where \( R \) is a \((q \times p)\) matrix of restrictions with \( \text{rank}(R) = p \). The estimator \( \hat{\pi} \) is obtained from a sample of \( N \) independent observations drawn from a common (unknown) multivariate distribution function. Assume also that \( \sqrt{N}(\hat{\pi} - \pi) \) is asymptotically multivariate normally distributed, with mean zero and positive definite variance-covariance matrix \( \Omega \).

The minimum distance estimator \( \hat{\Theta} \) of \( \Theta \) is defined as the solution of the following minimization problem:

\[
\min C(\Theta) = (\hat{\pi} - R\Theta)' \hat{\Omega}^{-1} (\hat{\pi} - R\Theta) \tag{5.E2}
\]
where \( \hat{\Omega}^{-1} \) converges to \( \Omega^{-1} \) in probability. In simple words, this means that the minimum distance estimator minimizes the "squared" (it is the solution of a quadratic form) weighted (by the matrix \( \hat{\Omega}^{-1} \)) distance between \( \hat{\pi} \) and \( \hat{\theta} \).

Following Hsiao (1986, pp.66-68), three basic properties of the minimum distance estimator can be derived:

1) The minimum distance estimator is consistent, that is \( \hat{\theta} \) converges to \( \theta \) in probability.

2) \( \sqrt{N}(\hat{\theta} - \theta) \) is asymptotically multivariate normally distributed, with mean zero and variance-covariance matrix \( (R'\Omega^{-1}R)^{-1} \).

3) \( C(\hat{\theta}) \) converges to a chi-square distribution, with \( q - p \) degrees of freedom.

Property 2 implies that the solution to the above minimization problem is provided by the generalized least squares estimator of \( \theta \):

\[
\hat{\theta} = (R'\hat{\Omega}^{-1}R)^{-1}R'\hat{\Omega}^{-1}\hat{\pi}.
\] (5.E3)

The problem is now to find appropriate estimates for \( \hat{\pi} \) and \( \hat{\Omega} \) in order to satisfy all the assumptions underlying the minimum distance estimation problem. If \( \hat{\pi} \) is a maximum likelihood estimator of \( \pi \), it can be proved that (Hsiao, 1986, pp.59-60):

1) \( \hat{\pi} \) is a consistent estimator of \( \pi \);

2) the central-limit theorem implies that \( \sqrt{N}(\hat{\pi} - \pi) \) is asymptotically normally distributed, with mean zero and positive definite variance-covariance matrix \( \Omega \);

3) the variance-covariance matrix \( \hat{\Omega} \) produced by maximum likelihood estimation is a consistent estimator of \( \Omega \).

---

65 In a more general version of the problem, \( \hat{\Omega}^{-1} \), the matrix appearing in the objective function, can be assumed to converge in probability to an arbitrary positive definite matrix \( \Psi \). Hsiao (1986, p.67) proves that an optimal choice for \( \Psi \) is \( \Omega^{-1} \), the inverse of the asymptotic variance-covariance matrix of \( \sqrt{N}(\hat{\pi} - \pi) \).
Maximum likelihood estimators of $\hat{\alpha}$ and $\hat{\Omega}$ therefore, satisfy the assumptions of the model. In my application of the minimum distance principle in Sub-Section 5.4.2, I use (a transformation of) OLS rather than maximum likelihood estimators for $\hat{\alpha}$ and $\hat{\Omega}$. However, under the general assumptions of the wage regression model introduced in Section 5.2, OLS and maximum likelihood estimates coincide.

The minimum distance estimator is efficient only relative to the class of estimators that do not impose a priori restrictions on the variance-covariance matrix of the error process. If the error term has a known structure, the minimum distance estimator, ignoring this specific structure, cannot be efficient, although it remains consistent (Hsiao, 1986, p.63).
Appendix 5.F: MATLAB Program for the Minimum Distance Chi-Square Test

i) MATLAB M-file: TESTMDE.M

```
% TESTMDE = test based on MDE
%
% This program runs the MDE (Minimum Distance Estimator) test of the
% null hypothesis that a # of vectors of estimated coefficients are
% equal. It collects the input vectors and var-cov matrices for the
% test. Function called: MDE(c1,G11,c2,G22,c3,G33,c4,G44,c5,G55).
% Up to 5 vectors of coefficients can be jointly compared.

n = input('Enter the # of vectors of coeff.s to be compared [2,5] ');
c1 = input('Enter the 1st vector of coeff.s c1 [vector-name or [...] trans] ');
G11 = input('Enter the 1st var-cov matrix G11 [matrix-name or [...] ] ');
c2 = input('Enter the 2nd vector of coeff.s c2 [vector-name or [...] trans] ');
G22 = input('Enter the 2nd var-cov matrix G22 [matrix-name or [...] ] ');
if n == 2
    mde (c1, G11, c2, G22)
elseif n == 3
    c3 = input('Enter the 3rd vector of coeff.s c3 [vector-name or [...] trans] ');
    G33 = input('Enter the 3rd var-cov matrix G33 [matrix-name or [...] ] ');
    mde (c1, G11, c2, G22, c3, G33)
elseif n == 4
    c3 = input('Enter the 3rd vector of coeff.s c3 [vector-name or [...] trans] ');
    G33 = input('Enter the 3rd var-cov matrix G33 [matrix-name or [...] ] ');
    c4 = input('Enter the 4th vector of coeff.s c4 [vector-name or [...] trans] ');
    G44 = input('Enter the 4th var-cov matrix G44 [matrix-name or [...] ] ');
    mde (c1, G11, c2, G22, c3, G33, c4, G44)
elseif n == 5
    c3 = input('Enter the 3rd vector of coeff.s c3 [vector-name or [...] trans] ');
    G33 = input('Enter the 3rd var-cov matrix G33 [matrix-name or [...] ] ');
    c4 = input('Enter the 4th vector of coeff.s c4 [vector-name or [...] trans] ');
    G44 = input('Enter the 4th var-cov matrix G44 [matrix-name or [...] ] ');
    c5 = input('Enter the 5th vector of coeff.s c5 [vector-name or [...] trans] ');
    G55 = input('Enter the 5th var-cov matrix G55 [matrix-name or [...] ] ');
    mde (c1, G11, c2, G22, c3, G33, c4, G44, c5, G55)
end
```

ii) MATLAB M-file: MDE.M

```
function chat = mde(c1, G11, c2, G22, c3, G33, c4, G44, c5, G55)

% MDE = MINIMUM DISTANCE ESTIMATOR
%
% MDE(c1, G11, c2, G22, c3, G33, c4, G44, c5, G55) compares
```
up to 5 vectors of coefficients (c1, c2, c3, c4, c5) with
the method of the minimum distance estimator. (G11, G22, G33,
G44, G55) are the estimated var-cov matrices associated
with the estimated coefficients (c1, c2, c3, c4, c5) respectively.

Inputs are the vectors (c1, c2, c3, c4, c5) and the respective
var-cov matrices (G11, G22, G33, G44, G55).

Output is the statistic CHAT, which is distributed as a Chi-square
with \((m-1)*p\) degrees of freedom, where:
\(m = \#\ of\ vectors\ to\ be\ compared\)
\(p = \#\ of\ elements\ in\ each\ of\ the\ vectors\ to\ be\ compared.\)

The method of minimum distance works with the following steps:
1) estimate the coefficients to be compared and their var-cov
matrices (done elsewhere, e.g. using OLS)
2) estimate by GLS:
\[
\begin{align*}
\text{betahat} &= \text{inv}(K' * \text{GINV} * K) * K' * \text{GINV} * \text{gammahat} \\
\text{where: gammahat} &= \text{stack of the vectors of coefficients to be} \\
& \quad \text{compared, dimensions (mp x 1)} \\
\text{K} &= \text{stack of identity matrices, dimensions (mp x p)} \\
\text{GINV} &= \text{block-diagonal matrix with the inverses of the} \\
& \quad \text{estimated var-cov matrices on the diagonal,} \\
& \quad \text{dimensions (mp x mp)}
\end{align*}
\]
3) estimate:
\[
\begin{align*}
\text{C} &= (\text{gammahat} - K * \text{beta})' * \text{GINV} * (\text{gammahat} - K * \text{beta}) \\
& \quad \text{substituting beta with betahat from the previous step. This} \\
& \quad \text{gives CHAT, the minimized value of C.}
\end{align*}
\]

\[
p = \max(\text{size}(c1));
\]
\[
m = \text{nargin}/2;
\]
\[
mp = m*p;
\]
\[
gammahat = c1;
\]
if \(m == 2\)
\[
\text{gammahat} = [\text{gammahat} ; c2];
\]
elseif \(m == 3\)
\[
\text{gammahat} = [\text{gammahat} ; c2 ; c3];
\]
elseif \(m == 4\)
\[
\text{gammahat} = [\text{gammahat} ; c2 ; c3 ; c4];
\]
elseif \(m == 5\)
\[
\text{gammahat} = [\text{gammahat} ; c2 ; c3 ; c4 ; c5];
\]
end
\[
K1 = \text{eye}(p);
\]
\[
K = K1;
\]
for \(i = 2:m\)
\[
K = [K : K1];
\]
end
clear i
if m==2
    G11INV = inv(G11);
    G22INV = inv(G22);
    GINV = [G11INV zeros(p);
            zeros(p) G22INV];
elseif m==3
    G11INV = inv(G11);
    G22INV = inv(G22);
    G33INV = inv(G33);
    GINV = [G11INV zeros(p) zeros(p);
            zeros(p) G22INV zeros(p);
            zeros(p) zeros(p) G33INV];
elseif m==4
    G11INV = inv(G11);
    G22INV = inv(G22);
    G33INV = inv(G33);
    G44INV = inv(G44);
    GINV = [G11INV zeros(p) zeros(p) zeros(p);
            zeros(p) G22INV zeros(p) zeros(p);
            zeros(p) zeros(p) G33INV zeros(p);
            zeros(p) zeros(p) zeros(p) G44INV];
elseif m==5
    G11INV = inv(G11);
    G22INV = inv(G22);
    G33INV = inv(G33);
    G44INV = inv(G44);
    G55INV = inv(G55);
    GINV = [G11INV zeros(p) zeros(p) zeros(p) zeros(p);
            zeros(p) G22INV zeros(p) zeros(p) zeros(p);
            zeros(p) zeros(p) G33INV zeros(p) zeros(p);
            zeros(p) zeros(p) zeros(p) G44INV zeros(p);
            zeros(p) zeros(p) zeros(p) zeros(p) G55INV];
end
betahat = inv(K' * GINV * K) * K' * GINV * gammahat;
chat = (gammahat - K*betahat)' * GINV * (gammahat - K*betahat);
References


Chapter 6

Summary and Conclusions

In Chapter 2 I have introduced the theoretical framework for the interpretation of the inter-industry wage differentials anomaly and illustrated the empirical strategy to tackle the issue of their measurement. Among competitive theories of wage determination, I have described human capital theory and the theory of compensating differentials. Among non-competitive theories, efficiency wage models and the insider-outsider theory have been considered. Three aspects of the industry differentials anomaly are presented: the existence of differentials at any one time in a given country, their persistence, and their similarity across countries. The various competitive and non-competitive theories are then evaluated in terms of their ability to explain these three aspects. The structure of the econometric model used to measure inter-industry wage differentials has been derived from the background of earnings functions of human capital theory. Its limitations have also been assessed. I have then discussed the role of labour market institutions - in particular, the degree of centralization of wage bargaining - in accounting for the observed pattern of industry wages and the relationship between institutional settings and alternative theories of wage determination.

Chapter 3 has shown how the significance, persistence over time and similarity across countries of inter-industry wage differentials based on aggregate data sources may have incorrectly been overrated. The Chapter is essentially devoted to measurement methods. In the existing literature, the degree of stability of industry differentials over time and across countries has been calculated through simple and rank correlations and the coefficient of concordance. The three metrics have been assessed in terms of their statistical properties and the statistical significance of results based on them has been carefully evaluated. The lack of significance of many results casts some doubts on the generally accepted conclusion that inter-industry wage differentials are remarkably stable over time and across countries. The Chapter has also suggested that average industry wages from aggregate data sources do not
represent the most suitable source of information about inter-industry differences, since they do not take into account the actual distribution of (observable) labour quality across industries.

Chapter 4 has investigated the inter-industry wage structure in the 1984 wave of the German Socio-Economic Panel (SOEP) and compared the main findings with those available for the U.S., Australia, Austria and Sweden. In contrast with what has emerged from aggregate data, empirical evidence based on individual data emphasizes cross-country differences. Earnings functions of human capital theory enriched with a set of industry dummy variables are estimated using Heckman's two-stage estimator to correct for possible sample selection bias due to the exclusion of overtime workers. Although in the German case industry differentials appear somehow significant, labour quality and other compensating factors have a major impact in explaining the wage structure, thus suggesting the possibility that industry differences just reflect the effect of unobservable characteristics. The comparisons of inter-industry wage structures across the five countries also suggests that the degree of centralization of wage bargaining may play a role in accounting for the observed pattern of industry wages, with large and significant differentials in more decentralized labour markets and small and largely insignificant differentials in centralized settings.

In Chapter 5 I have extended the analysis presented in Chapter 4 by directly estimating the inter-industry wage structure in five countries - the U.S., Canada, Australia, Germany and the Netherlands - using the individual data of the "Luxembourg Income Study" (LIS) databank. This approach allows to overcome a number of limitation encountered in the previous Chapter when comparing directly estimated results with results published in the literature by other authors. The measurement method is again the estimate of earnings functions enriched with a set of dummy variables for industry affiliation. Cross-country comparisons have relied both on traditional correlation coefficients and on a more rigorous chi-square test based on the Minimum Distance Estimator (MDE) technique. Similarly to what has emerged in Chapter 4 and in contrast with evidence from aggregate data sources, empirical evidence from micro data has highlighted cross-country dissimilarities. The pattern of inter-industry wage differentials across countries seems to reflect again institutional conditions such as the degree of centralization of wage bargaining.

Empirical evidence of the existence and importance of inter-industry wage differentials in an international perspective provides a general picture which seems more complex than the one initially suggested both by human capital theorists and by the earliest advocates of
efficiency wage and insider-outsider models. In the thesis I have tried to address two aspects of the industry wage differentials anomaly: the existence of significant industry differentials in a given year for a variety of countries and their similarity across these countries when differentials are estimated with individual data in a regression approach that takes into account differences in individual (observable) characteristics.

The evidence presented here provides a further test of the generality of the hypothesis that industries matter in the process of wage determination. The hypothesis is rejected. In various cases inter-industry wage differentials are rather small and/or insignificant. If industry differentials are the empirical anomaly we need to account for with an appropriate theoretical rationalization, then we are left with very little to be explained by non-competitive theories of the labour market. In countries where inter-industry wage differentials are indeed significant, the evidence does not allow to discriminate among alternative explanations in an uncontroverisal way. Industry differentials seem to be larger and more significant in decentralized labour markets and this outcome might be consistent with the efficiency wage hypothesis. The insider-outsider hypothesis instead does not seem to receive equally supportive evidence from significant differentials in centralized labour markets. However, according to the two theories, the hypothetical relationship between inter-industry wage differentials and the degree of centralization of wage bargaining rests, in both cases, on rather restrictive assumptions. Efficiency wage and insider-outsider considerations may affect the structure of industry wages through other channels which are independent of institutional conditions and hence neither model of wage determination can be ruled out on the basis of the results above.

Competitive theories would instead imply that estimated inter-industry wage differentials just reflect unobservable labour quality non-uniformly distributed across industry sectors. This probably remains the most serious objection about the interpretation of inter-industry wage differentials. However, certain aspects of my results may be regarded as casting at least some doubts on the standard competitive model. The cross-country pattern of industry wage structures shows clear differences in the relative impact on wages of labour quality and industry variables. The impact of observable labour quality measures is stronger in centralized than in decentralized labour markets. This is true both when a great variety of such controls is taken into account and when a much smaller set of controls is included in estimated wage equations. In fact, the two types of estimates (with many and few control
variables) produce rather similar results in terms of size of inter-industry wage differentials in a certain number of countries. Unless one believes that unobservable characteristics are far more important than observable ones and totally uncorrelated with them, these results seem hard to reconcile with the competitive view.

Contrary to what tends to emerge from aggregate average data, evidence from individual data shows that different countries do look different. Micro data permit, to a certain extent, to correct for labour quality inequalities. Evidence of this kind from heterogeneous cross-sectional studies indicates clear inter-country differences in the relative importance of labour quality and industry variables in explaining the observed wage structure. This conclusion is confirmed by cross-sectional estimates based on a more homogeneous data source. Moreover, differences among countries in the size and significance of inter-industry wage differentials appear to reflect some underlying institutional aspect of the labour market, like the degree of centralization of wage bargaining procedures.

One may object that more decentralized, flexible labour markets tend to reward observable and unobservable labour quality to a greater extent than centralized, less flexible markets. If this is the case, the unobservable labour quality bias affecting estimated inter-industry wage differentials would be larger in decentralized than in centralized countries.

In the end, the kind of wage equations estimated in this thesis, as well as in a huge number of other cross-sectional studies, typically explain between 30 and 40 percent only of the total variability of wages, thus leaving room for a variety of possible criticisms. The only way out of this problem would be a different approach based on longitudinal data that allows to correct for time-invariant labour characteristics, like innate ability. Panel data studies for the United States have provided controversial results. The same type of evidence for Germany could have been produced from the SOEP, but since Germany exhibits almost insubstantial inter-industry wage differentials even in a cross-sectional analysis, little could be gained from this more sophisticated (and computationally much more onerous) approach. Comparing panel evidence from heterogeneous sources raises the same kind of problems encountered in cross-sectional comparisons. As far as a unique source of longitudinal individual data for multiple countries is not available (and the LIS data-bank is not this kind of source), it is rather difficult to pursue the argument beyond the results presented in this thesis. Future availability of this type of data would therefore be crucial for a more general evaluation of the inter-industry wage differentials anomaly.
Appendix

Alternative Parameterizations
of Dummy Variable Models

A.1 Introduction

In the empirical literature on inter-industry wage differentials, the standard approach consists in the estimate of cross-section wage functions derived from human capital theory and the evaluation of the influence of industry affiliation on relative wages. The impact of industry affiliation is estimated by adding a set of industry dummy variables to a wage equation already including various controls for human capital, demographic characteristics, and working conditions (Krueger and Summers, 1988). Estimated industry wage differentials are then normalised as deviations from the (weighted) mean differential, following the procedure suggested by Krueger and Summers,

"Since the wage regressions include a constant, we treated the omitted industry variable as having a zero effect on wages, calculate the employment-weighted average of wage differentials for all industries, and report the difference between the industry differentials and the weighted average. The resulting statistics are the proportionate difference in wages between an employee in a given industry and the average employee." (Krueger and Summers, 1988, p.263).

Since Krueger and Summers' seminal article, nearly every study of the inter-industry wage structure has adopted the same approach (among the others, Borland and Suen, 1990; Edin and Zetterberg, 1992; Winter-Ebmer, 1992; Chapter 4 and Chapter 5 in this thesis). This simple algebraic transformation of estimated industry coefficients presents a double advantage. Firstly, wage differentials are "normalised", in the sense that they express wage differences in percentage points with respect to the average employee in the whole economy, rather than
relative to some arbitrary group of employees. The resulting differentials are therefore more easily interpretable. Secondly, wage differentials become independent of the arbitrarily chosen base industry - the omitted industry dummy - and therefore they can be directly compared across studies using different industries as reference groups.

The case of inter-industry wage differentials is just an example of the several types of wage differentials (by gender, race, occupation, etc.) that have been extensively analysed in the labour economics literature. All of them are essentially derived from the estimate of a wage equation which includes a number of dummies among the explanatory variables. It is also an example of a more general econometric issue, the existence of alternative ways to parameterize a model which includes dummy variables among the regressors. In this Appendix I will show how estimated industry dummy coefficients and wage differentials normalised à la Krueger and Summers correspond to the parameters of two alternative specifications of the same theoretical model. In particular, the usually estimated wage regressions - which include a constant and omit one of the industry dummies - represent a specific parameterization of such a model, while wage differentials as deviations from the (weighted) mean differential actually derive from a more general parameterization of the same model. Although the two specifications present identical statistical properties, the general parameterization produces results which are more useful and easier to interpret from an economic point of view (Suits, 1984).

This Appendix illustrates the relationships between all the possible, alternative parameterizations of a dummy variable model and provides formulae to switch from one parameterization to another without actually re-estimating the model. Moreover, it presents algorithms to transform accordingly the variance-covariance matrix of the estimated parameters, so that inference procedures can be established in each case. This last point has been neglected by Krueger and Summers, who, after having suggested the normalisation of industry differentials, confess,

"The standard errors we report, however, are the unadjusted OLS standard errors." (Krueger and Summers, 1988, p.263).

Needless to say, many other authors after them have followed their example. This approach essentially implies the use of the standard errors estimated form a specific model to construct
t-tests for the parameters of the general model. In principle, the procedure is incorrect and, in practice, it may give rise to differences in the evaluation of the statistical significance of single normalised differentials which are of considerable size (see Chapter 5 in this thesis).

The rest of this Appendix is structured as follows. Section A.2 illustrates the nature of the alternative parameterizations of a model with dummy variables among its regressors. Section A.3 examines the relationships between the various parameterizations and presents formulae which formalize these relationships in general terms. Section A.4 provides formulae for the corresponding transformation of the variance-covariance matrices of the estimated coefficients. Section A.5 gives a numerical illustration of the general results presented in the previous Sections for the case of wage equations. Section A.6 contains some concluding remarks.

A.2 Alternative Parameterizations of a Model with Dummy Variables

To discuss the effects of alternative specifications of models including dummy variables among the regressors, I consider an equation that contains both quantitative explanatory variables and qualitative dummy (zero-one) variables. The set of dummy variables represents some characteristic of the dependent variable, which can assume a finite number of alternative states.

Let us first consider the model in its general form:

\[ y_i = \alpha + x_i'\beta + d_i'\delta + u_i, \quad i = 1, ..., N, \]  

where \( y_i \) is the dependent variable, \( \alpha \) is an intercept term, \( x_i \) is a \((M \times 1)\) vector of continuous explanatory variables, \( \beta \) is a \((M \times 1)\) vector of unknown parameters for these explanatory variables, \( d_i \) is a \(((K+1) \times 1)\) vector of \((K+1)\) dummy (zero-one) variables, \( \delta \) is a \(((K+1) \times 1)\) vector of unknown parameters for the dummy variables, and \( u_i \) is a disturbance term assumed to be \( u_i \sim IN(0, \sigma_u^2) \).
The set of dummy variables here represents the total \((K+1)\) possible states taken by the characteristic of interest. This implies the following structure of the vector \(d_i\):

\[
d_i = \begin{bmatrix}
d_{i1} \\
d_{i2} \\
\vdots \\
d_{ik} \\
d_{ik+1}
\end{bmatrix},
\]

where \(d_{ik}, k = 1, \ldots, K+1\), are the dummy (zero-one) variables. The number of elements equal to 1 for the variable \(d_{i1}, i = 1, \ldots, N\), i.e., the number of observations belonging to the 1st category in terms of the characteristic of interest - is \(n_1\); the number of elements equal to 1 for the variable \(d_{i2}, i = 1, \ldots, N\), i.e., the number of observations belonging to the 2nd category in terms of the characteristic of interest - is \(n_2\); and so on for the other dummy variables up to \(d_{ik+1}\), so that \(n_1 + n_2 + \ldots + n_{k+1} = N\). Accordingly, the vector of parameters \(\delta\) is:

\[
\delta = \begin{bmatrix}
\delta_1 \\
\delta_2 \\
\vdots \\
\delta_k \\
\delta_{k+1}
\end{bmatrix}
\]

The model in general form includes both an intercept term and the parameters for all \((K+1)\) dummies. This type of specification leads to the following interpretation of the parameters in equation (A.1): the intercept term \(\alpha\) represents the overall expected value (level) of the dependent variable, for \(x_i = 0\), and the parameters \(\delta\) measure the differentials.
with respect to such expected value due to the different states assumed by the characteristic of interest. Note that all \((K+1)\) categories are directly represented in equation (A.1). The relationship described by model (A.1) can be illustrated graphically as shown in Figure A.1. Let us assume that \(M = 1\) - i.e., \(x_i\) is \((1\times 1)\) and model (A.1) has only one continuous explanatory variable - and that \(K = 2\) - i.e., there are three categories in terms of the characteristic of interest and model (A.1) contains three dummy variables. Equation (A.1) depicts four regression lines combined into a single equation. The continuous line is an overall base line for the model \(\hat{y}_i = \hat{\alpha} + \hat{\beta}x_i\), while the three dashed lines represent the three different categories and their deviations from the base line \((\delta_1, \delta_2, \text{and } \delta_3)\). The dashed lines, in fact, go through the points of means calculated over the sub-samples for the 1st, 2nd, and 3rd category, \((\bar{x}_1, \bar{y}_1)\), \((\bar{x}_2, \bar{y}_2)\), and \((\bar{x}_3, \bar{y}_3)\) respectively.

The parameters in model (A.1), however, cannot be uniquely estimated by OLS. In fact, for each \(i = 1, \ldots, N\), the set of the regressors includes both a one, so that the corresponding parameter is an intercept term, and all \((K+1)\) dummies, which sum to unity. This is the well-known problem of perfect multicollinearity among regressors called dummy trap. Any constant added to the parameters \(\delta\) and subtracted from \(\alpha\) produces a set of
coefficients which satisfies the least squares criterion (Suits, 1984). In terms of the regression lines in Figure A.1 this means that, although the dashed lines are uniquely identified by the relationship between $y$ and $x$ for each of the three categories, the continuous base line can lie anywhere. Therefore, in order to estimate a dummy variable model, we need to impose some restriction on the parameters $\alpha$ and $\delta$.

The practical way out of this problem is usually to reformulate equation (A.1) as one of the two alternative specific reparameterizations:

$$
y_i = \alpha^* + x_i' \beta + \delta^*_i + u_i, \quad i = 1, \ldots, N
$$

(A.2)

or

$$
y_i = x_i' \beta + \delta^*_i + u_i, \quad i = 1, \ldots, N
$$

(A.3)

where $y_i$, $x_i$, $\beta$, and $u_i$ are defined as in equation (A.1), $\alpha^*$ is an intercept term, $\delta^*_i$ is a $(K\times1)$ vector of $K$ dummy variables, $\delta^*$ is a $(K\times1)$ vector of unknown parameters for the dummy variables in the vector $\delta^*_i$, $d^*_i$ is a $((K+1)\times1)$ vector of $(K+1)$ dummy variables, and $\delta^*$ is a $((K+1)\times1)$ vector of unknown parameters for the dummy variables in the vector $d^*_i$.

The two sets of dummy variables in $d^*_i$ and $d^*_i$ represent respectively the first $K$ and the total $(K+1)$ possible states assumed by the characteristic of interest. The structure of the vectors $d^*_i$ and $d^*_i$ is therefore:
Consequently, the vectors of parameters $\delta^*$ and $\delta^*$ are respectively:

$$
\delta^* = \begin{bmatrix}
\delta_1^* \\
\delta_2^* \\
\vdots \\
\delta_K^* \\
\delta_{K+1}^*
\end{bmatrix}, \quad \delta^* = \begin{bmatrix}
\delta_1 \\
\delta_2 \\
\vdots \\
\delta_K \\
\delta_{K+1}
\end{bmatrix}
$$

The reparameterization of model (A.1) illustrated by model (A.2) involves an intercept term and the parameters for the first $K$ dummies only. Alternatively, the reparameterization represented by model (A.3) involves no intercept and the parameters for all $(K+1)$ dummies. So, with respect to the general model (A.1), equation (A.2) implies the linear restriction $\delta_{K+1} = 0$ and equation (A.3) the linear restriction $\alpha = 0$ (Suits, 1984; Kennedy, 1986).

The dummy variables are the same as in model (A.1), but the respective parameters will not have the same meaning. In model (A.2), the intercept $\alpha^*$ represents the expected value (level) of the dependent variable for the observations in the $(K+1)^{th}$ category in terms of the characteristic of interest - the category which corresponds to the omitted dummy $d_{K+1}$ - when $x_i = 0$, and the parameters $\delta^*$ measure the differential effects for the $1^{st}$, $2^{nd}$, ..., $K^{th}$ categories compared with the $(K+1)^{th}$ category. Model (A.2) is depicted in Figure A.2, again under the assumptions $M = 1$ and $K = 2$, so that it includes only the first two dummy variables. Equation (A.2) combines three regression lines: a base line (continuous), which
represents the 3rd category and goes through the point of means \((\bar{x}_3, \bar{y}_3)\) calculated over the sub-sample for this category \((\hat{y}_i = \hat{\alpha} + \hat{\beta} x_i)\); and two lines (dashed), which represent the 1st and 2nd category - they go through the points of means calculated over the sub-samples for the 1st and 2nd category, \((\bar{x}_1, \bar{y}_1)\) and \((\bar{x}_2, \bar{y}_2)\) - and their differentials with respect to the 3rd category \((\delta_1^* \text{ and } \delta_2^*)\).

FIGURE A.2
Model (A.2)

In model (A.3) instead, the parameters \(\mathbf{\delta}^*\) simply represent the expected values (levels) of the dependent variable for the observations in each of the 1st, 2nd, ..., Kth, (K+1)th categories, when \(x_i = 0\). Model (A.3) is shown in Figure A.3. Equation (A.3), which includes all three dummy variables, combines four regression lines: a base line (continuous) constrained through the origin \((\hat{y}_i = \hat{\beta} x_i)\), and three lines (dashed) again representing each category and going through the points of means of the respective sub-samples. The lines for the three categories of observations are obviously the same for all models, since model (A.1), (A.2), and (A.3) are simple reparameterizations of the same basic relationship.
The parameters in model (A.2) and model (A.3) can be uniquely estimated by OLS, since in both cases the values corresponding to the group of regressors do not form a linearly dependent combination.

A.3 Relationships between the Alternative Parameterizations

From the estimate of model (A.2) or model (A.3) we can reconstruct the estimates of the parameters in model (A.1), but not uniquely. As already observed, there is an infinite number of solutions for the parameters in model (A.1) in terms of the parameters in either model (A.2) or model (A.3). An interesting possibility I will consider is when, in model (A.1), the parameter \( \alpha \) represents the mean of the dependent variable - for \( x_i = 0 \) - over the observations in all \((K+1)\) categories defined in terms of the characteristic of interest, and the parameters \( \delta \) measure the differential effects for each of the \((K+1)\) categories compared with this overall mean. In this case the parameters of the dummy variables can be interpreted as the differentials associated to each category with respect to the relationship between \( y \) and \( x \) that holds over the population as a whole, rather than relative to some arbitrary category (Suits, 1984). Given this definition of the parameters \( \delta \), this implies the imposition of the
identifying restriction $\sum \delta_k s_k = 0$ on model (A.1), where $s_k$, $k = 1, \ldots, K+1$, are the proportions of observations in the $(K+1)$ categories (Kennedy, 1986). And in terms of the regression lines in Figure A.1, this entails the continuous base line $\hat{y}_i = \hat{a} + \hat{\beta} x_i$ going through the point of means $(\bar{x}, \bar{y})$ calculated over the entire sample.

A.3.1 Relationship between Model (A.1) and Model (A.2)

Let us first consider the relationship between model (A.1), thus characterized, and model (A.2). Given the estimates $\delta^*$ from model (A.2), I define the weighted average of differentials for model (A.2) as:

$$\hat{WA}^* = \frac{\sum_{j=1}^{K+1} n_j \delta_j^*}{\sum_{j=1}^{K+1} n_j} = \frac{\sum_{j=1}^{K} n_j \delta_j^*}{N}, \quad (A.4)$$

where the weight for each estimated coefficient $\delta_j^*, j = 1, \ldots, K$, is the proportion of observations belonging to the $j^{th}$ category. The omitted dummy $d_{K+1}$ for the $(K+1)^{th}$ category is treated as having a zero differential effect on the dependent variable, so that this category does not affect the numerator of $\hat{WA}^*$. However, its size $n_{K+1}$ does enter the denominator of $\hat{WA}^*$. The estimated intercept term of model (A.1) is then defined as:

$$\hat{a} = \hat{a}^* + \hat{WA}^* \quad (A.5)$$
and its regression coefficients $\delta$ as:

$$
\delta_i = \delta^*_i - \tilde{WA}^* \\
\delta_k = \delta^*_k - \tilde{WA}^* \\
\delta_{k+1} = -\tilde{WA}^*.
$$

(A.6)

The coefficients $\hat{\beta}$ for the explanatory variables $x_i$ remain unaffected by the previous transformations.

Thus, in the estimated model (A.1), the regression constant ($\hat{\alpha}$) is given by the sum of the mean of the dependent variable - when $x_i = 0$ - for the $(K+1)^{\text{th}}$ category ($\hat{\alpha}^*$) plus the (weighted) average differential for the first $K$ categories with respect to the $(K+1)^{\text{th}}$ ($\tilde{WA}^*$): it therefore represents the mean of the dependent variable - when $x_i = 0$ - for all $(K+1)$ categories, weighted by the relative size of each category, i.e., the mean of the dependent variable for the whole sample. And the coefficients for the dummy variables ($\delta_k$) are given by the differences between each of the differentials with respect to the $(K+1)^{\text{th}}$ category ($\delta^*_k$) and their own (weighted) average ($\tilde{WA}^*$): they therefore measure differential effects which are no longer compared with the $(K+1)^{\text{th}}$ category, but relative to the whole sample.

The weighted average $\tilde{WA}^*$ in equation (A.4) can be expressed in matrix form as:

$$
\tilde{WA}^* = s^* \delta^*,
$$

(A.7)

where $s^*$ is the $(K \times 1)$ vector.
and its elements are the relative sizes of each of the first \( K \) categories in terms of the characteristic of interest:

\[
s_k = \frac{n_k}{\sum_{j=1}^{K+1} n_j} = \frac{n_k}{N}, \quad k = 1, \ldots, K.
\]

Substituting equation (A.7) into (A.5), I find the following final expression for the estimated intercept term of model (A.1):

\[
\hat{\alpha} = \hat{\alpha}^* + s^* \delta^*.
\]  

(A.8)

From the set of equations (A.6), the relationship between \( \delta \) and \( \delta^* \) can be expressed in matrix form as follows:

\[
\delta = Z \delta^* - \hat{\alpha}^*.
\]  

(A.9)

where \( \hat{\alpha}^* \) is a \((K+1) \times 1\) vector of elements all equal to \( \hat{\alpha}^* \) and \( Z \) is a \((K+1) \times K\) matrix constructed as the stack of a \(K \times K\) identity matrix and a \(1 \times K\) row of zeros.
The matrix $Z$ has in practice the effect of transforming the $(K\times 1)$ vector $\delta^*$ into a $(K+1)\times 1$ vector, the $(K+1)^{th}$ element of which is a zero:

$$Z = \begin{bmatrix} 1 & 0 & 0 & \ldots & 0 \\ 0 & 1 & 0 & \ldots & 0 \\ 0 & 0 & 1 & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \ldots & 1 \\ 0 & 0 & 0 & \ldots & 0 \end{bmatrix}$$

The vector $\widehat{\omega}^*$ appearing in equation (A.9) can in turn be rewritten as:

$$Z\delta^* = \begin{bmatrix} \delta_1^* \\ \delta_2^* \\ \vdots \\ \delta_K^* \\ 0 \end{bmatrix}$$

The vector $\widehat{\omega}^*$ appearing in equation (A.9) can in turn be rewritten as:

$$\widehat{\omega}^* = es' \delta^*, \quad (A.10)$$

where $e$ is a $(K+1)\times 1$ vector of ones. Substituting equation (A.10) into (A.9), I find the following final expression for the regression coefficients $\hat{\delta}$ of model (A.1):

$$\hat{\delta} = (Z - es' \delta^*), \quad (A.11)$$

338
Using (A.8) and (A.11) and observing that \( d'_i Z = d'_i \) and that \( d'_i e = 1 \). I can summarize the steps of the reparameterization which leads from model (A.1) to model (A.2):

\[
\begin{align*}
\hat{y}_i &= \hat{a} + x'_i \hat{\beta} + d'_i \hat{\delta} \\
&= \hat{a} + x'_i \hat{\beta} + d'_i (Z - es') \hat{\delta}^* \\
&= \hat{a} + x'_i \hat{\beta} + d'_i Z \hat{\delta}^* - d'_i es' \hat{\delta}^* \\
&= \hat{a} - s' \hat{\delta}^* + x'_i \hat{\beta} + d'_i \hat{\delta}^* \\
&= \hat{a} + x'_i \hat{\beta} + d'_i \hat{\delta}^*.
\end{align*}
\] (A.12)

With reference to the case of inter-industry wage differentials, it should be now clear that the industry dummy coefficients initially estimated by Krueger and Summers (1988) correspond to the coefficients \( \hat{\delta}^* \) from model (A.2), while the normalised industry wage differentials subsequently calculated and presented by them correspond to the first \( K^6 \) of the \((K+1)\) coefficients \( \hat{\delta} \) from model (A.1). Equation (A.11) therefore represents a convenient way to operate the same transformation and obtain all \((K+1)\) normalised differentials.

### A.3.2 Relationship between Model (A.1) and Model (A.3)

Let us now turn to the relationship between model (A.1) and model (A.3). From the estimates \( \hat{\delta}^* \) of model (A.3), I define the *weighted average of levels* of the dependent variable for model (A.3) as:

---

\(^{66}\) Krueger and Summers (1988) do not present the normalised wage differential for their base industry - the omitted industry dummy - which should be equal to \(-\hat{\delta}^*\). This is because the corresponding "unadjusted OLS standard error", the statistic they provide in all the tables, is obviously not defined. The unadjusted OLS standard errors are in fact the standard errors of the industry dummy coefficients \( \hat{\delta}^* \) from model (A.2), where the base industry dummy is omitted. An "adjusted" standard error for the wage differential of the base industry can be obtained only using the transformations on variance-covariance matrices presented later in Section A.4. In that Section, I will show how to derive standard errors which refer directly to the coefficients \( \hat{\delta} \) from model (A.1).
where the weight for each estimated coefficient $\hat{\delta}_j^*, j = 1, ..., K+1$, is again the proportion of observations belonging to the $j^{th}$ category. The estimated intercept term of model (A.1) is then defined as:

$$\hat{\alpha} = \bar{W}_A^*$$  \hspace{1cm} (A.14)

and its regression coefficients $\hat{\delta}$ as:

$$\hat{\delta}_1 = \hat{\delta}_1^* - \bar{W}_A^*$$

$$\ldots \ldots \ldots \ldots$$

$$\hat{\delta}_{K+1} = \hat{\delta}_{K+1}^* - \bar{W}_A^*.$$  \hspace{1cm} (A.15)

Like in the previous case, the coefficients $\hat{\beta}$ for the explanatory variables $x_i$ remain unaffected by these transformations.

The regression constant of model (A.1) ($\hat{\alpha}$) is now the average of the expected levels of the dependent variable - when $x_i = 0$ - for all $(K+1)$ categories, weighted by the relative size of each category ($\bar{W}_A^*$): it therefore represents the overall mean of the dependent variable - when $x_i = 0$ - for the whole sample. The coefficients for the dummy variables ($\hat{\delta}_k$) are here given by the differences between each of the expected levels of the dependent
variable - when \( x_i = 0 \) - for the \((K+1)\) categories \( (\delta^*_k) \) and their own (weighted) average \( (\bar{W}A^*) \): they therefore measure differential effects with respect to the mean of the dependent variable for the entire sample.

The weighted average \( \bar{W}A^* \) in equation (A.13) can also be expressed in matrix form as:

\[
\bar{W}A^* = s^*\delta^*,
\]

where \( s^* \) is the \(((K+1)\times1)\) vector:

\[
s^* = [s_1, s_2, \ldots, s_{K+1}]
\]

and its elements \( s_k, k = 1, \ldots, K+1 \), are now the relative sizes of all \((K+1)\) categories. Substituting equation (A.16) into (A.14), I obtain the following final expression for the estimated intercept term of model (A.1):

\[
\hat{\alpha} = s^*\delta^*.
\]

From the set of equations (A.15), the relationship between \( \delta \) and \( \delta^* \) can be expressed in matrix form as follows:
\[ \delta = \delta^* - \widehat{w}a^*, \]  

where \( \widehat{w}a^* \) is a \(((K+1) \times 1)\) vector of elements all equal to \( \widehat{W}a^* \). The vector \( \widehat{w}a^* \) can in turn be rewritten as:

\[ \widehat{w}a^* = e s'^* \delta^*, \]  

where \( e \) is defined as before. Substituting equation (A.19) into (A.18), I obtain the following final expression for the regression coefficients \( \delta \) of model (A.1):

\[ \delta = (I - es'^*) \delta^*, \]  

where \( I \) is a \(((K+1) \times (K+1))\) identity matrix.

Using (A.17) and (A.20) and observing that \( d_i = d_i^* \) and that again \( d_i' e = 1 \), I can summarize the steps of the reparameterization which leads from model (A.1) to model (A.3):

\[ \begin{align*}
\hat{y}_i &= \hat{\alpha} + x_i' \hat{\beta} + d_i' \delta \\
&= \hat{\alpha} + x_i' \hat{\beta} + d_i'(I - es'^*) \delta^* \\
&= \hat{\alpha} + x_i' \hat{\beta} + d_i' \delta^* - d_i' es'^* \delta^* \\
&= \hat{\alpha} - s'^* \delta^* + x_i' \hat{\beta} + d_i' \delta^* \\
&= x_i' \hat{\beta} + d_i' \delta^*. 
\end{align*} \]  

Again with reference to the case of inter-industry wage differentials, equation (A.20) provides an easy method to obtain the industry wage differentials \( \delta \) normalised à la Krueger

342
and Summers (1988), starting from the alternative specification of the original wage function represented by model (A.3) and its coefficients \( \delta^* \).

A.3.3 Relationship between Model (A.2) and Model (A.3)

Because of the relationship existing between model (A.2) and model (A.3), these two alternative transformations of the estimates of model (A.2) and model (A.3) lead to exactly the same values for the estimates of model (A.1). From the estimates \( \hat{\alpha}^* \) and \( \hat{\delta}^* \) of model (A.2) we can in fact derive the estimates \( \delta^* \) of model (A.3) as:

\[
\begin{align*}
\hat{\delta}_1^* &= \hat{\delta}_1^* + \hat{\alpha}^* \\
\vdots & \quad \vdots \\
\hat{\delta}_k^* &= \hat{\delta}_k^* + \hat{\alpha}^* \\
\hat{\delta}_{k+1}^* &= \hat{\alpha}^*
\end{align*}
\]

or, in matrix notation:

\[
\hat{\delta}^* = Z \hat{\delta}^* + e \hat{\alpha}^*,
\]

(A.23)

where \( Z \) and \( e \) are defined as before. Conversely, from the estimates \( \hat{\delta}^* \) of model (A.3) we can derive the estimates \( \hat{\alpha}^* \) and \( \hat{\delta}^* \) of model (A.2) as:

\[
\hat{\alpha}^* = \hat{\delta}_{k+1}^*
\]

(A.24)

and
or, in matrix notation:

\[
\delta^* = A \delta^*,
\]

(A.26)

where \( A \) is a \((K \times (K+1))\) matrix constructed from the horizontal concatenation of a \((K \times K)\) identity matrix and a \((K \times 1)\) column of minus ones:

\[
A = \begin{bmatrix}
1 & 0 & 0 & \ldots & 0 & 0 & 1 \\
0 & 1 & 0 & \ldots & 0 & 0 & -1 \\
0 & 0 & 1 & \ldots & 0 & -1 & \vdots \\
\vdots & \vdots & \vdots & \ldots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & \ldots & 1 & -1
\end{bmatrix}
\]

The coefficients \( \hat{\beta} \) for the explanatory variables \( x_i \) remain unaffected by these transformations. Finally, the relationship between the two weighted averages \( \widehat{WA}^* \) and \( \widehat{WA}^\ast \) is:

\[
\widehat{WA}^\ast = \widehat{WA}^* + \hat{\alpha}^*
\]

(A.27)

or alternatively, being \( \hat{\alpha}^* = \hat{\delta}_{K+1}^* \):
Model (A.2) and model (A.3) are hence a reparameterization of each other. Using (A.23) and observing that \( \hat{d}_i'Z = d_i'^e \) and that \( d_i'^e = 1 \), I can summarize the steps of the reparameterization which leads from model (A.3) to model (A.2):

\[
\hat{y}_i = x_i'\hat{\beta} + \hat{d}_i'^e \hat{\delta}^*
\]
\[
= x_i'\hat{\beta} + \hat{d}_i'^e (Z\hat{\delta}^* + \eta \hat{\epsilon}^*)
\]
\[
= x_i'\hat{\beta} + \hat{d}_i'^e Z\hat{\delta}^* + \hat{d}_i'^e \eta \hat{\epsilon}^*
\]
\[
= \hat{\alpha}^* + x_i'\hat{\beta} + \hat{d}_i'^e \hat{\delta}^*.
\]

On the other hand, using (A.24) and (A.26) and observing that \( \hat{d}_i'^e = \hat{d}_i'Z \), that \( ZA\hat{\delta}^* = \hat{\delta}^* - \eta \hat{\epsilon}^* \delta_{x+1} \), and that again \( \hat{d}_i'^e = 1 \), I can summarize the steps of the reparameterization which leads from model (A.2) to model (A.3):

\[
\hat{y}_i = \hat{\alpha}^* + x_i'\hat{\beta} + \hat{d}_i'^e \hat{\delta}^*
\]
\[
= \delta_{x+1}^* + x_i'\hat{\beta} + \hat{d}_i'^e ZA\hat{\delta}^*
\]
\[
= \delta_{x+1}^* + x_i'\hat{\beta} + \hat{d}_i'^e (\hat{\delta}^* - \eta \hat{\epsilon}^* \delta_{x+1}^*)
\]
\[
= \delta_{x+1}^* + x_i'\hat{\beta} + \hat{d}_i'^e \hat{\delta}^* - \hat{d}_i'^e \eta \hat{\epsilon}^* \delta_{x+1}^*
\]
\[
= \delta_{x+1}^* - \delta_{x+1}^* + x_i'\hat{\beta} + \hat{d}_i'^e \hat{\delta}^*
\]
\[
= x_i'\hat{\beta} + \hat{d}_i'^e \hat{\delta}^*.
\]

We have thus seen all the possible transformations of the regression coefficients that, starting from the estimate of either model (A.2) or model (A.3), permit to reconstruct the
estimates of model (A.1) in its general form and to switch from model (A.2) to model (A.3) and vice versa.

A.4 Variance-Covariance Matrices for the Estimators of the Alternative Parameterizations

To establish inference procedures and test hypotheses about the parameters in any of the three models seen above, we need the variance-covariance matrices of the respective OLS estimators. Starting from the estimates of either model (A.2) or model (A.3), I will now reconstruct the variance-covariance matrix of the coefficients in model (A.1). I will also consider the transformations required to derive the variance-covariance matrix of the OLS estimators when switching from model (A.2) to model (A.3) and vice versa.

The variance-covariance matrix of the estimated coefficients in model (A.1) is a \((M+K+2)\times(M+K+2)\) matrix that can be written in partitioned form as:

\[
\begin{bmatrix}
\text{Var}(\hat{\alpha}) & \text{Cov}(\hat{\alpha}, \hat{\beta}) & \text{Cov}(\hat{\alpha}, \hat{\delta}) \\
\text{Cov}(\hat{\beta}, \hat{\alpha}) & \text{Var-Cov}(\hat{\beta}) & \text{Cov}(\hat{\beta}, \hat{\delta}) \\
\text{Cov}(\hat{\delta}, \hat{\alpha}) & \text{Cov}(\hat{\delta}, \hat{\beta}) & \text{Var-Cov}(\hat{\delta})
\end{bmatrix}
\]

where \(\text{Var}(\hat{\alpha})\) is the variance of the estimated intercept \(\hat{\alpha}\), \(\text{Var-Cov}(\hat{\beta})\) is the \((M\times M)\) variance-covariance matrix of the \(M\) coefficients in the vector \(\hat{\beta}\), \(\text{Var-Cov}(\hat{\delta})\) is the \(((K+1)\times(K+1))\) variance-covariance matrix of the \((K+1)\) coefficients in the vector \(\hat{\delta}\), \(\text{Cov}(\hat{\beta},\hat{\alpha}) = \text{Cov}(\hat{\alpha},\hat{\beta})'\) is the \((M\times 1)\) vector of covariances between each of the \(M\) coefficients in \(\hat{\beta}\) and \(\hat{\alpha}\), \(\text{Cov}(\hat{\delta},\hat{\alpha}) = \text{Cov}(\hat{\alpha},\hat{\delta})'\) is the \(((K+1)\times 1)\) vector of covariances between each of the \((K+1)\) coefficients in \(\hat{\delta}\) and \(\hat{\alpha}\), and \(\text{Cov}(\hat{\delta},\hat{\beta}) = \text{Cov}(\hat{\beta},\hat{\delta})'\) is the
A \((K+1)\times M\) matrix of covariances between each of the \((K+1)\) coefficients in \(\hat{\delta}\) and each of the \(M\) coefficients in \(\hat{\beta}\).

If model (A.2) is estimated by OLS, we obtain, from most computer programs, the estimate of the variance-covariance matrix of its coefficients, which is a \(((M+K+1)\times(M+K+1))\) matrix that can be written in partitioned form as:

\[
\begin{bmatrix}
\text{Var}(\hat{\alpha}^*) & \text{Cov}(\hat{\alpha}^*,\hat{\beta}) & \text{Cov}(\hat{\alpha}^*,\hat{\delta}^*) \\
\text{Cov}(\hat{\beta},\hat{\alpha}^*) & \text{Var-Cov}(\hat{\beta}) & \text{Cov}(\hat{\beta},\hat{\delta}^*) \\
\text{Cov}(\hat{\delta}^*,\hat{\alpha}^*) & \text{Cov}(\hat{\delta}^*,\hat{\beta}) & \text{Var-Cov}(\hat{\delta}^*)
\end{bmatrix}
\]

where \(\text{Var}(\hat{\alpha}^*)\) is the variance of the estimated intercept \(\hat{\alpha}^*\), \(\text{Var-Cov}(\hat{\beta})\) is the \((M\times M)\) variance-covariance matrix of the \(M\) coefficients in the vector \(\hat{\beta}\), \(\text{Var-Cov}(\hat{\delta}^*)\) is the \((K\times K)\) variance-covariance matrix of the \(K\) coefficients in the vector \(\hat{\delta}^*\), \(\text{Cov}(\hat{\beta},\hat{\alpha}^*) = \text{Cov}(\hat{\alpha}^*,\hat{\beta})^t\) is the \((M\times1)\) vector of covariances between each of the \(M\) coefficients in \(\hat{\beta}\) and \(\hat{\alpha}^*\), \(\text{Cov}(\hat{\delta}^*,\hat{\alpha}^*) = \text{Cov}(\hat{\alpha}^*,\hat{\delta}^*)^t\) is the \((K\times1)\) vector of covariances between each of the \(K\) coefficients in \(\hat{\delta}^*\) and \(\hat{\alpha}^*\), and \(\text{Cov}(\hat{\delta}^*,\hat{\beta}) = \text{Cov}(\hat{\beta},\hat{\delta}^*)^t\) is the \((K\times M)\) matrix of covariances between each of the \(K\) coefficients in \(\hat{\delta}^*\) and each of the \(M\) coefficients in \(\hat{\beta}\). I can thus derive the variances and covariances of the estimated coefficients of model (A.1), as appearing in the matrix (A.31), in terms of the sub-matrices contained in the matrix (A.32). Using equation (A.8), the variance of the estimated constant term \(\hat{\alpha}\) of model (A.1) can be obtained as:

\[
\text{Var}(\hat{\alpha}) = \text{Var}(\hat{\alpha}^*) + s^*\text{Var-Cov}(\hat{\delta}^*)s^* + 2s^*\text{Cov}(\hat{\delta}^*,\hat{\alpha}^*).
\]
And applying equation (A.11), the variance-covariance matrix of the coefficients in the vector $\hat{\delta}$ of model (A.1) can be derived as:

$$Var-Cov(\delta) = (Z - es^*)Var-Cov(\delta^*)(Z - es')' = (Z - es')Var-Cov(\delta^*)(Z' - s^*e').$$ (A.34)

Finally, using again equations (A.8) and (A.11), and recalling that the coefficients $\hat{\beta}$ are unaffected by the transformations on the other coefficients of model (A.2), I can derive the sub-matrices of covariances $Cov(\hat{\beta}, \hat{\alpha})$, $Cov(\hat{\delta}, \hat{\alpha})$, and $Cov(\hat{\delta}, \hat{\beta})$ for model (A.1):

$$Cov(\hat{\beta}, \hat{\alpha}) = Cov(\hat{\beta}, \alpha^*) + Cov(\hat{\beta}, \delta^*)s^*;$$ (A.35)

$$Cov(\hat{\delta}, \hat{\alpha}) = (Z - es^*)Cov(\delta^*, \alpha^*) + (Z - es^*)Var-Cov(\delta^*)s^*;$$ (A.36)

$$Cov(\hat{\delta}, \hat{\beta}) = (Z - es^*)Cov(\delta^*, \hat{\beta}).$$ (A.37)

Note that the variance-covariance matrix of the coefficients in the vector $\hat{\beta}$ of model (A.1) remains unchanged with respect to the same matrix for model (A.2).

From equation (A.34), we can see how the difference between each element of $Var-Cov(\delta)$ and the corresponding elements of $Var-Cov(\delta^*)$ depends on the various elements of the matrix $Var-Cov(\delta^*)$, the variances and covariances of the $K$ coefficients in the vector $\delta^*$, and on the elements of the vector $s^*$, the proportions of observations in the first $K$ categories in terms of the characteristic of interest. The difference is smaller, the smaller the (absolute) size of the elements of $Var-Cov(\delta^*)$ and/or $s^*$. In particular, for any given matrix $Var-Cov(\delta^*)$, the difference tends to zero as the elements of $s^*$ tend to zero.
This means that when $K$ is large (i.e., we have many categories in terms of the characteristic of interest) and the distribution of observations across the $K$ categories is sufficiently uniform (i.e., the proportions of observations in all categories are sufficiently small), the difference between $\text{Var-Cov}(\delta)$ and $\text{Var-Cov}(\delta^*)$ may be negligible. If this is not the case, the sign of the difference between $\text{Var-Cov}(\delta)$ and $\text{Var-Cov}(\delta^*)$, and in particular between their diagonal elements, is instead unpredictable. That is, we cannot establish \textit{a priori} whether the variances of the coefficients $\delta$ are larger or smaller than the corresponding variances of the coefficients $\delta^*$. The directions of these inequalities depend in fact on a combination of several factors, such as the relative magnitude of the proportions in $s^*$, the relative magnitude of the variances and covariances in $\text{Var-Cov}(\delta)$, and the sign of these covariances.

With reference to the case of inter-industry wage differentials, the incorrect procedure adopted by Krueger and Summers (1988) consists in comparing the first $K$ coefficients $\delta$ from model (A.1) with the standard errors derived from the diagonal elements of the $(K \times K)$ sub-matrix $\text{Var-Cov}(\delta^*)$ of model (A.2), in order to evaluate the statistical significance of individual wage differentials. The practical implications of this approach obviously depend on the actual difference between $\text{Var-Cov}(\delta)$ - the sub-matrix which Krueger and Summers should have used to derive appropriate standard errors - and $\text{Var-Cov}(\delta^*)$. As we have just seen, such difference largely depends on the size of the elements of $s^*$, which in this context represent the proportions of workers employed in each industry. The results presented by the authors in their Table I (Krueger and Summers, 1988, p.264) are likely to be considerably affected by the incorrect procedure. Here the authors estimate wage differentials using the one-digit census industry classification (CIC), which leads to the definition of only 7 very aggregate industries. The shares of employees by industry (the elements of $s^*$) are therefore rather large and so is likely to be the difference between $\text{Var-Cov}(\delta)$ and $\text{Var-Cov}(\delta^*)$. As already noticed, the sign of the difference is however unpredictable and depends on the specific values assumed by the variances and covariances of the estimated industry dummy coefficients $\delta^*$ and by the employment shares $s^*$ in this particular case. Consequently, we
cannot evaluate a priori whether the authors’ conclusion about the overall strong significance of individual differentials would be weakened or strengthened, were the correct approach adopted instead. The consequences of the incorrect procedure are probably less serious in the case of the results presented by Krueger and Summers in their Table II (Krueger and Summers, 1988, pp.265-266). Here the authors consider wage differentials for 42 two-digit CIC industries, a much more disaggregate classification. Some - but not all - employment shares by industry become much smaller and so is likely to become, to some extent, the difference between \( \text{Var-Cov}(\hat{\delta}) \) and \( \text{Var-Cov}(\hat{\delta}^*) \). This conclusion is indirectly supported by the evidence provided in Chapter 4 for the case of the German inter-industry wage structure. In Chapter 4, a similar two-digit industry classification is utilized and the resulting employment shares range from 0.5% to 13.9%. In these circumstances, the difference between the standard errors derived from \( \text{Var-Cov}(\hat{\delta}) \) and those derived from \( \text{Var-Cov}(\hat{\delta}^*) \) is only of order \( 10^3 \) and does not affect the overall judgement about the statistical significance of individual wage differentials. The problem is likely to be even less serious for the set of results presented by Krueger and Summers in their Appendix Table A1 (Krueger and Summers, 1988, pp.281-287). Here an extremely disaggregate three-digit industry classification is considered (216 CIC industries). Employment shares should be rather small and the difference between \( \text{Var-Cov}(\hat{\delta}) \) and \( \text{Var-Cov}(\hat{\delta}^*) \) probably negligible. In any case, however, the fact that the distribution of workers across industries cannot be expected to be nearly uniform\(^{67}\) casts some doubts on the reliability of all three sets of results.

Let us now consider the derivation of the variances and covariances of the coefficients of model (A.1) starting from the variance-covariance matrix of the OLS estimators for model (A.3), which is a \( ((M+K+1)\times(M+K+1)) \) matrix that can be written in partitioned form as:

\[
\begin{bmatrix}
\text{Var-Cov}(\hat{\beta}) & \text{Cov}(\hat{\beta},\hat{\delta}^*) \\
\text{Cov}(\hat{\delta}^*,\hat{\beta}) & \text{Var-Cov}(\hat{\delta}^*)
\end{bmatrix}
\]

(A.38)

\(^{67}\) Unfortunately, exact employment shares by industry are never provided by Krueger and Summers (1988).
where \( \text{Var-Cov}(\hat{\beta}) \) is the \((M \times M)\) variance-covariance matrix of the \( M \) coefficients in the vector \( \hat{\beta} \). \( \text{Var-Cov}(\delta^*) \) is the \(((K+1) \times (K+1))\) variance-covariance matrix of the \((K+1)\) coefficients in the vector \( \delta^* \), and \( \text{Cov}(\delta^*,\hat{\beta}) = \text{Cov}(\hat{\beta},\delta^*)' \) is the \(((K+1) \times M)\) matrix of covariances between each of the \((K+1)\) coefficients in \( \delta^* \) and each of the \( M \) coefficients in \( \hat{\beta} \). Using equation (A.17), the variance of the estimated constant term \( \hat{\alpha} \) of model (A.1) can be obtained as:

\[
\text{Var}(\hat{\alpha}) = s'' \text{Var-Cov}(\delta^*)s'.
\]

(A.39)

And applying equation (A.20), the variance-covariance matrix of the coefficients in the vector \( \hat{\delta} \) of model (A.1) can be derived as:

\[
\text{Var-Cov}(\hat{\delta}) = (I - es'^*) \text{Var-Cov}(\delta^*) (I - es'^*)'
\]

\[
= (I - es'^*) \text{Var-Cov}(\delta^*) (I - s' e').
\]

(A.40)

Finally, using again equations (A.17) and (A.20), and recalling that the coefficients \( \hat{\beta} \) are unaffected by the transformations on the other coefficients of model (A.3), I can derive the sub-matrices of covariances \( \text{Cov}(\hat{\beta},\hat{\alpha}) \), \( \text{Cov}(\hat{\delta},\hat{\alpha}) \), and \( \text{Cov}(\hat{\delta},\hat{\beta}) \) for model (A.1):

\[
\text{Cov}(\hat{\beta},\hat{\alpha}) = \text{Cov}(\hat{\beta},\delta^*) s';
\]

(A.41)

\[
\text{Cov}(\hat{\delta},\hat{\alpha}) = (I - es'^*) \text{Var-Cov}(\delta^*) s';
\]

(A.42)

\[
\text{Cov}(\hat{\delta},\hat{\beta}) = (I - es'^*) \text{Cov}(\delta^*,\hat{\beta}).
\]

(A.43)
Similarly to the case of equation (A.34), equation (A.40) shows how the difference between each element of $V_{\text{ar-Cov}}(\delta)$ and the corresponding elements of $V_{\text{ar-Cov}}(\delta^*)$ depends on the various elements of the matrix $V_{\text{ar-Cov}}(\delta^*)$, the variances and covariances of the $(K+1)$ coefficients in the vector $\delta^*$, and on the elements of the vector $s^*$, the proportions of observations in all $(K+1)$ categories in terms of the characteristic of interest.

The difference is smaller, the smaller the (absolute) size of the elements of $V_{\text{ar-Cov}}(\delta^*)$ and/or $s^*$. Again, for any given matrix $V_{\text{ar-Cov}}(\delta^*)$, the difference tends to zero as the elements of $s^*$ tend to zero.

Because of the relationship between model (A.2) and model (A.3), the variance-covariance matrix of the coefficients of either model can be derived directly from the variance-covariance matrix of the coefficients of the other. Let us suppose we estimate model (A.2) by OLS and obtain the estimates of the sub-matrices contained in the variance-covariance matrix (A.32). Using equation (A.23), I can find the variance-covariance matrix of the coefficients in the vector $\mathbf{\delta}$ of model (A.3) as:

$$
V_{\text{ar-Cov}}(\mathbf{\delta}) = ZV_{\text{ar-Cov}}(\mathbf{\delta}^*)Z' + ZCov(\delta^*,\hat{\alpha}^*)e' + \\
+ eCov(\hat{\alpha}^*,\delta^*)Z' + eVar(\hat{\alpha}^*)e'
$$

(A.44)

and the sub-matrix of covariances $Cov(\delta^*,\hat{\beta})$ for model (A.3) as:

$$
Cov(\delta^*,\hat{\beta}) = ZCov(\delta^*,\hat{\beta}) + eCov(\hat{\alpha}^*,\hat{\beta}).
$$

(A.45)
Conversely, we can estimate model (A.3) and obtain the estimates of the sub-matrices contained in the variance-covariance matrix (A.38). Using equation (A.24), the variance of the estimated constant term $\hat{\alpha}^{*}$ of model (A.2) will simply be:

\[
Var(\hat{\alpha}^{*}) = Var(\hat{\delta}_{K+1}^{*}).
\]  

(A.46)

where $Var(\hat{\delta}_{K+1}^{*})$ is the $((K+1),(K+1))^{th}$ element of the sub-matrix $Var-Cov(\hat{\delta}^{*})$. And using equation (A.26), I can find the variance-covariance matrix of the coefficients in the vector $\hat{\delta}^{*}$ of model (A.2) as:

\[
Var-Cov(\hat{\delta}^{*}) = A Var-Cov(\hat{\delta}^{*})A'.
\]  

(A.47)

Finally, using both equations (A.24) and (A.26), I can find the sub-matrices of covariances $Cov(\hat{\beta},\hat{\alpha}^{*})$, $Cov(\hat{\delta}^{*},\hat{\alpha}^{*})$, and $Cov(\hat{\delta}^{*},\hat{\beta})$ for model (A.2):

\[
Cov(\hat{\beta},\hat{\alpha}^{*}) = Cov(\hat{\beta},\hat{\delta}_{K+1}^{*}),
\]  

(A.48)

where $Cov(\hat{\beta},\hat{\delta}_{K+1}^{*})$ is the $(K+1)^{th}$ column of the sub-matrix $Cov(\hat{\beta},\hat{\delta}^{*})$;

\[
Cov(\hat{\delta}^{*},\hat{\alpha}^{*}) = ACov(\hat{\delta}^{*},\hat{\delta}_{K+1}^{*}),
\]  

(A.49)

where $Cov(\hat{\delta}^{*},\hat{\delta}_{K+1}^{*})$ is the $(K+1)^{th}$ column of the sub-matrix $Var-Cov(\hat{\delta}^{*})$;

353
\[ \text{Cov}(\hat{\delta}^*, \hat{\beta}) = A \text{Cov}(\delta^*, \beta). \] (A.50)

Again, the variance-covariance matrix of the coefficients in the vector \( \hat{\beta} \) remains unchanged.

We have thus seen how, with relatively simple algebraic transformations, it is possible to reconstruct the variance-covariance matrix of the coefficients of model (A.1), which cannot be directly estimated. I have also illustrated the relationship between the variance-covariance matrices of the coefficients of model (A.2) and model (A.3), so that from the estimates of either model, the variance-covariance matrix of the other can be derived without re-estimating it.

### A.5 A Numerical Example

As a simple illustration, I apply the transformations presented in Sections A.3 and A.4 to a set of "artificial" data\(^{68}\) on individual wages and human capital/demographic characteristics, listed in the internal Appendix. Let us suppose we are interested in evaluating wage differentials across different ethnic groups. Conventional wage equations are estimated, at an individual level, regressing the logarithm of the hourly wage rate \((\ln W/H)\) on two human capital controls - education \((EDUC)\) and experience in the labour market \((EXP)\) - and on a set of dummy variables for the ethnicity of the individuals in the sample \((D_{\text{BLACK}}, D_{\text{HISP}}, D_{\text{WHITE}})\). The possible alternative states assumed by the characteristic of interest - ethnicity - are three: black, hispanic, and white. Therefore, in the current example, \(M = 2\) and \(K = 2\). The numbers of black, hispanic, and white individuals are \(n_{\text{BLACK}} = 7\), \(n_{\text{HISP}} = 2\), and \(n_{\text{WHITE}} = 11\), respectively; the total number of observations in the sample is hence \(N = 20\); and the relative sizes of the three categories in terms of ethnicity are \(s_{\text{BLACK}} = 0.35\), \(s_{\text{HISP}} = 0.10\), and \(s_{\text{WHITE}} = 0.55\).

\(^{68}\) The small data-set of 20 observations used in this illustrative example has been created by the author (see internal Appendix). In terms of the type of variables and the values chosen, this data might be seen as mimicking certain features of the United States labour market. Anyhow, the limited and specific nature of the data employed does not affect in any way the generality of the results presented in this Section.
The OLS estimate of model (A.2), which includes an intercept term and only two dummy variables for the ethnicity - black and hispanic - gives the following results (standard errors of the estimated coefficients in parentheses):

\[
\ln \frac{W_i}{H_i} = 1.8227 + 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i - 0.1016 D_{\text{BLACK}_i} - 0.2865 D_{\text{HISP}_i}.
\]

The estimated intercept term (1.8227) is the predicted level of the (log-hourly) wage of white workers with no education and no experience; the coefficient for the first dummy variable (-0.1016) is the estimated wage differential for black workers with respect to white workers, at any given levels of education and experience; the coefficient for the second dummy variable (-0.2865) is the estimated wage differential for hispanic workers with respect to white workers, at any given levels of education and experience. In other words, according to these results, black workers are estimated to earn about 10% less than white workers with the same education and experience and hispanic workers about 29% less than white workers with the same education and experience. The estimate of model (A.2) depicts in fact three different wage equations combined into a single equation:

\[
\ln \frac{W_i}{H_i} = 1.8227 + 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i
\]

(A.2'.i)

\[
\ln \frac{W_i}{H_i} = 1.8227 + 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i - 0.1016
\]

(A.2'.ii)

\[
\ln \frac{W_i}{H_i} = 1.8227 + 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i - 0.2865
\]

(A.2'.iii)

The first estimated function (A.2'.i) is representative of white workers - the reference group, i.e. the group for which the ethnicity dummy variable has been omitted - and, in graphical
terms, goes through the point of means calculated over the sub-sample of white workers 
\( \ln \bar{W}_{\text{WHITE}} = 2.70, \quad \overline{EDUC}_{\text{WHITE}} = 12.18, \quad \overline{EXP}_{\text{WHITE}} = 15.09 \). The second estimated function (A.2'.ii) is representative of black workers and goes through the point of means calculated over the sub-sample of black workers \( \ln \bar{W}_{\text{BLACK}} = 2.36, \quad \overline{EDUC}_{\text{BLACK}} = 9.29, \quad \overline{EXP}_{\text{BLACK}} = 9.00 \). The third estimated function (A.2'.iii) is representative of hispanic workers and goes through the point of means calculated over the sub-sample of hispanic workers \( \ln \bar{W}_{\text{HISP}} = 2.01, \quad \overline{EDUC}_{\text{HISP}} = 7.00, \quad \overline{EXP}_{\text{HISP}} = 6.00 \). The second and the third function are hence expressed in relative terms, \textit{with respect to the equation for white workers.}

From the estimated coefficients for the dummy variables in equation (A.2'), I can compute the \textit{weighted average of differentials} between wages:

\[
\bar{W}^* = \frac{-0.1016 \times 7 - 0.2865 \times 2 + 0 \times 11}{7 + 2 + 11} = -0.0642,
\]

(A.4')

which expresses the average wage differential for \textit{all the workers} in the sample \textit{with respect to white workers} - therefore the differential for white workers is equal to zero in this formula - at any given levels of education and experience.

From the estimate of model (A.2) I also obtain the following variance-covariance matrix of the coefficients, according to the partitioning used for the matrix (A.32) in Section A.4:

\[
\begin{pmatrix}
0.02359 & -0.00239 & 0.00040 & -0.00494 & -0.00921 \\
-0.00239 & 0.00028 & -0.00007 & 0.00040 & 0.00083 \\
0.00040 & -0.00007 & 0.00003 & -0.00002 & -0.00009 \\
-0.00494 & 0.00040 & -0.00002 & 0.00211 & 0.00229 \\
-0.00921 & 0.00083 & -0.00009 & 0.00229 & 0.00626
\end{pmatrix}
\]

(A.32')
A conventional $t$-test concerning each of the dummy parameters in model (A.2) tests whether the wage of black and/or hispanic workers is significantly different from the wage of white workers. So equation (A.2') shows that the wage of black workers is significantly different from the wage of white workers at the 5% level (but not at the 1% level), while the wage of hispanic workers is significantly different from that of white workers at both the 5% and 1% level.

Alternatively, the OLS estimate of model (A.3), which implies no intercept term and all the dummy variables for the ethnicity - black, hispanic, and white - gives:

\[
\ln \frac{W_i}{H_i} = 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i + 1.7211 \text{D BLACK}_i + 1.5362 \text{D HISP}_i + 1.8227 \text{D WHITE}_i.
\]  
(A.3')

The coefficient for the first dummy variable (1.7211) is the predicted level of the (log-hourly) wage of black workers with no education and no experience; the coefficient for the second dummy variable (1.5362) is the predicted level of the (log-hourly) wage of hispanic workers with no education and no experience; and the coefficient for the third dummy variable (1.8227) is the predicted level of the (log-hourly) wage of white workers with no education and no experience. The estimate of model (A.3) also depicts three wage functions combined into a single equation:

\[
\ln \frac{W_i}{H_i} = 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i + 1.7211 
\]  
(A.3'.i)

\[
\ln \frac{W_i}{H_i} = 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i + 1.5362 
\]  
(A.3'.ii)

\[
\ln \frac{W_i}{H_i} = 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i + 1.8227 
\]  
(A.3'.iii)
The first equation (A.3'.i) is representative of black workers and goes through the point of means calculated over the sub-sample of black workers ($\ln W/H_{\text{BLACK}}, \overline{EDUC_{\text{BLACK}}}, \overline{\text{EXP}_{\text{BLACK}}}$ defined as before). The second equation (A.3'.ii) is representative of Hispanic workers and goes through the point of means calculated over the sub-sample of Hispanic workers ($\ln W/H_{\text{HISP}}, \overline{EDUC_{\text{HISP}}}, \overline{\text{EXP}_{\text{HISP}}}$). The third equation (A.3'.iii) is representative of white workers and goes through the point of means calculated over the sub-sample of white workers ($\ln W/H_{\text{WHITE}}, \overline{EDUC_{\text{WHITE}}}, \overline{\text{EXP}_{\text{WHITE}}}$). These three wage functions, in a sense, are also expressed in relative terms, with respect to a base function constrained through the origin:

$$\ln W/H_i = 0.0557 \overline{EDUC_i} + 0.0133 \overline{\text{EXP}_i}$$  \hspace{1cm} (A.3'.iv)

which goes through the point ($\ln W/H = 0, \overline{EDUC} = 0, \overline{\text{EXP}} = 0$). They are obviously the same three functions depicted by equation (A.2'), since model (A.3) is a simple reparameterization of model (A.2).

From the estimated coefficients for the dummy variables in equation (A.3'), I can compute the weighted average of levels of the wage variable:

$$\overline{WA} = 1.7211 \times 7 + 1.5362 \times 2 + 1.8227 \times 11 \overline{7 + 2 + 11} = 1.7585,$$ \hspace{1cm} (A.13')

which expresses the average (log-hourly) wage for all the workers in the sample, with no education and no experience.

From the estimate of model (A.3) I also obtain the following variance-covariance matrix of the coefficients, according to the partitioning used for the matrix (A.38) in Section A.4:
A t-test concerning each of the dummy parameters in model (A.3) tests whether the wage of black, hispanic and/or white workers is significantly different from the wage predicted by the base equation constrained through the origin. The results of equation (A.3') tell us that wages of black, hispanic, and white workers are all strongly significant. However, this equation does not provide any direct information about the existence of significant wage differentials across ethnic groups.

Following the analysis presented in Sub-Section A.3.3, I can verify the relationship existing between the coefficients in equations (A.2') and (A.3'). As illustrated by the set of equations (A.22), the coefficients of the dummy variables for black and hispanic workers in equation (A.3') are given by the sum of the corresponding coefficients in equation (A.2') and of the estimated constant in equation (A.2') \(1.7211 = -0.1016 + 1.8227\) and \(1.5362 = -0.2865 + 1.8227\); and the coefficient of the dummy variable for white workers in equation (A.3') is equal to the estimated constant of equation (A.2') \(1.8227\). Alternatively, we can look at this relationship as expressed by equations (A.24) and (A.25), according to which the estimated constant in equation (A.2') is equal to the coefficient of the dummy variable appearing in equation (A.3') but excluded from equation (A.2') - here the dummy for white workers \(1.8227\); and the coefficients of the dummy variables for black and hispanic workers in equation (A.2') are given by the difference between the corresponding coefficients in equation (A.3') and the coefficient of the third dummy variable in equation (A.3') \((-0.1016 = 1.7211 - 1.8227\) and \(-0.2865 = 1.5362 - 1.8227\). The coefficients for the human capital controls \(EDUC\) and \(EXP\) remain the same in the two equations.
The relationship between the weighted averages $\widehat{WA}^*$ and $\widehat{WA}'$, illustrated by equations (A.27) and (A.28), can be verified as follows:

\[
\widehat{WA}^* = \widehat{WA}' + \delta^* = -0.0642 + 1.8227 = 1.7585 ;
\]

\[
\widehat{WA}' = \widehat{WA}' - \delta_{K+1} = 1.7585 - 1.8227 = -0.0642 .
\]

Applying equations (A.44) and (A.45), I can derive the estimated variance-covariance matrix of the coefficients in equation (A.3') from the sub-matrices of the estimated variance-covariance matrix (A.32') for equation (A.2'):\[69\]

\[
\text{Var-Cov}(\delta^*) = \begin{bmatrix}
1 & 0 & 0.00211 & 0.00229 \\
0 & 1 & 0.00229 & 0.00626 \\
o & 0 & 0 & 0.00211 & 0.00229 \\
1 & 1 & 1 & 1 & 1
\end{bmatrix}
\]

\[
= \begin{bmatrix}
0.01583 & 0.01173 & 0.01865 \\
0.01173 & 0.01142 & 0.01437 \\
0.01865 & 0.01437 & 0.02359
\end{bmatrix}
\]

\[69\] All computations involving the equations appearing in Sections A.3 and A.4 were performed with MATLAB, Ver. 3.5j. Within MATLAB, the relative accuracy of numbers is approximately 16 significant decimal digits. Due to space limits, only the first 5 decimal digits are presented here. This may generate some imprecisions in the last decimal digit presented, caused by round-off.
Conversely, applying equations (A.46)-(A.50), I can switch from the estimated variance-covariance matrix (A.38') of the coefficients in equation (A.3') to the estimated variance-covariance matrix for equation (A.2'):

\[
\text{Var}(\hat{\alpha}^*) = \begin{bmatrix} 0.02359 \end{bmatrix},
\]

\[
\text{Var-Cov}(\hat{\delta}^*) = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & -1 \\ -0.00239 & 0.00040 & -0.00002 \end{bmatrix},
\]

\[
\text{Cov}(\hat{\beta}, \hat{\alpha}^*) = \begin{bmatrix} -0.00239 \\ 0.00040 \end{bmatrix},
\]

\[
\text{Cov}(\hat{\delta}^*, \hat{\alpha}^*) = \begin{bmatrix} 0.01583 \\ 0.01173 \\ 0.01865 \end{bmatrix},
\]

\[
\text{Cov}(\hat{\delta}^*, \hat{\beta}) = \begin{bmatrix} -0.00200 \\ -0.00156 \\ -0.00239 \end{bmatrix}.
\]

Note that the estimated variance-covariance sub-matrix of the coefficients for the human capital controls,
remains the same for the two estimated models.

Let us now consider the derivation of model (A.1), which includes both an intercept term and the three dummy variables for the ethnicity. From the estimates of model (A.2) and applying equations (A.8) and (A.11), the coefficients of model (A.1) can be reconstructed as follows:

\[
\ln \frac{\hat{W}}{H} = 1.7585 + 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i - 0.0374 \text{BLACK}_i - 0.2223 \text{HISP}_i + 0.0642 \text{WHITE}_i.
\]

Here the estimated intercept term (1.7585) is the predicted level of the (log-hourly) wage of the average worker in the whole sample with no education and no experience; the coefficient for the first dummy variable (-0.0374) is the estimated wage differential for black workers with respect to the average worker, at any given levels of education and experience; the coefficient for the second dummy variable (-0.2223) is the estimated wage differential for hispanic workers with respect to the average worker, at any given levels of education and experience; and the coefficient for the third dummy variable (+0.0642) is the estimated wage differential for white workers with respect to the average worker, at any given levels of education and experience. So the reparameterization represented by model (A.1) provides a set of results that are more useful and easier to interpret in terms of wage differentials by ethnicity. They show that black workers are estimated to earn about 4% less than the average, hispanic workers about 22% less than the average, and white workers about 6% more than the average. The estimate of model (A.1) depicts now four different wage equations:

\[
\ln \frac{\hat{W}}{H} = 1.7585 + 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i,
\]

(A.1':i)
\[ \ln \bar{W}/H_i = 1.7585 + 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i - 0.0374, \]  \hfill (A.1'\text{.ii})

\[ \ln \bar{W}/H_i = 1.7585 + 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i - 0.2223, \]  \hfill (A.1'\text{.iii})

\[ \ln \bar{W}/H_i = 1.7585 + 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i + 0.0642. \]  \hfill (A.1'\text{.iv})

The first estimated function \((A.1'\text{.i})\) is representative of the sample as a whole and goes through the point of means calculated over the entire sample \((\ln \bar{W}/H = 2.51, \text{EDUC} = 10.65, \text{EXP} = 12.05)\). The second, third, and fourth estimated function are, as before, representative of black, hispanic, and white workers respectively and go through the points of means calculated over the respective sub-samples. The second, third, and fourth function are thus expressed in relative terms with respect to an equation representing the whole sample of workers. Wage differentials associated to each ethnic group are measured against the wage of the average worker, rather than relative to some arbitrarily chosen reference group.

The coefficients in equation \((A.1')\) are obtained by applying the results presented in Sub-Section A.3.1. As illustrated by equation \((A.5)\), the estimated constant in equation \((A.1')\) is given by the sum of the estimated constant in equation \((A.2')\) and of the weighted average of differentials \(\bar{W}_A\ast\) \((1.7585 = 1.8227 + (-0.0642))\); and using the set of equations \((A.6)\), the coefficients of the first two dummy variables for black and hispanic workers in equation \((A.1')\) are calculated as the difference between the corresponding coefficients in equation \((A.2')\) and the weighted average of differentials \(\bar{W}_A\ast\) \((-0.0374 = -0.1016 - (-0.0642)\) and \(-0.2223 = -0.2865 - (-0.0642)\)), while the coefficient of the third dummy variable for white workers in equation \((A.1')\) is equal to minus the weighted average of differentials \(\bar{W}_A\ast\) \((0.0642 = - (-0.0642))\). The coefficients for the human capital controls are the same in equation \((A.1')\) and equation \((A.2')\).
The estimated variance-covariance matrix of the coefficients in equation (A.1'), according to the partitioning used for the matrix (A.31) in Section A.4, is:

\[
\begin{pmatrix}
0.01877 & -0.00217 & 0.00038 & -0.00180 & -0.00562 & 0.00217 \\
-0.00217 & 0.00028 & -0.00007 & 0.00017 & 0.00061 & -0.00022 \\
0.00038 & -0.00007 & 0.00003 & -0.00000 & -0.00007 & 0.00002 \\
-0.00180 & 0.00017 & -0.00000 & 0.00066 & 0.00037 & -0.00049 \\
-0.00562 & 0.00061 & -0.00007 & 0.00037 & 0.00389 & -0.00095 \\
0.00217 & -0.00022 & 0.00002 & -0.00049 & -0.00095 & 0.00048 \\
\end{pmatrix}
\text{(A.31')}

This variance-covariance matrix is derived from the estimated variance-covariance matrix (A.32') for equation (A.2'), applying equations (A.33)-(A.37) as illustrated below:

\[
\text{Var}(\hat{\beta}) = \begin{bmatrix} 0.02359 \end{bmatrix} + \begin{bmatrix} 0.35 & 0.10 \end{bmatrix} \begin{bmatrix} 0.00211 & 0.00229 \\ 0.00229 & 0.00626 \end{bmatrix} \begin{bmatrix} 0.35 \\ 0.10 \end{bmatrix} + 2 \cdot \begin{bmatrix} 0.35 & 0.10 \end{bmatrix} \begin{bmatrix} -0.00494 \\ -0.00921 \end{bmatrix} = \begin{bmatrix} 0.01877 \end{bmatrix},
\text{(A.33')}
\]

\[
\text{Var-Cov}(\hat{\delta}) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} - \begin{bmatrix} 0.35 \\ 0.10 \\ 1 \end{bmatrix} \begin{bmatrix} 0.00211 & 0.00229 \\ 0.00229 & 0.00626 \end{bmatrix} \begin{bmatrix} 0.35 \\ 0.10 \\ 1 \end{bmatrix} - 2 \cdot \begin{bmatrix} 0.35 \\ 0.10 \\ 1 \end{bmatrix} \begin{bmatrix} -0.00066 & 0.00037 & -0.00049 \\ 0.00037 & 0.00389 & -0.00095 \\ -0.00049 & -0.00095 & 0.00048 \end{bmatrix},
\text{(A.34')}
\]

\[
\text{Cov}(\hat{\beta}, \hat{\delta}) = \begin{bmatrix} -0.00239 \\ 0.00040 \end{bmatrix} + \begin{bmatrix} 0.00040 & 0.00083 \\ -0.00002 & -0.00009 \end{bmatrix} \begin{bmatrix} 0.35 \\ 0.10 \end{bmatrix} = \begin{bmatrix} -0.00217 \\ 0.00038 \end{bmatrix},
\text{(A.35')}
\]
\[ \text{Cov}(\hat{\beta},\hat{\alpha}) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 0.35 & 0.10 \end{bmatrix} = -0.00494 - 0.00921 + \\
+ \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 0.35 & 0.10 \end{bmatrix} \begin{bmatrix} 0.00211 & 0.00229 & 0.35 \\ 0.00229 & 0.00626 & 0.10 \end{bmatrix} = (A.36') \\
= \begin{bmatrix} -0.00180 \\
-0.00562 \\
0.00217 \end{bmatrix}, \]

\[ \text{Cov}(\hat{\beta},\hat{\beta}) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 0.35 & 0.10 \end{bmatrix} \begin{bmatrix} 0.00040 & -0.00002 \\ 0.00083 & -0.00009 \end{bmatrix} = (A.37') \\
= \begin{bmatrix} 0.00017 & -0.00000 \\
0.00061 & -0.00007 \\
-0.00022 & 0.00002 \end{bmatrix}. \]

The estimated variance-covariance sub-matrix of the coefficients for the human capital controls,

\[ \text{Var-Cov}(\hat{\beta}) = \begin{bmatrix} 0.00028 & -0.00007 \\ -0.00007 & 0.0003 \end{bmatrix}, \]

is the same for both equation (A.1') and equation (A.2').

Equation (A.1') can also be derived, with identical results, from the estimates of model (A.3) and applying equations (A.17) and (A.20). The relationship between the coefficients in equation (A.1') and equation (A.3') is as illustrated in Sub-Section A.3.2. Using equation (A.14), the estimated constant in equation (A.1') is set equal to the weighted average of wage levels $\widehat{\omega}^*(1.7585)$; and according to the set of equations (A.15), the coefficients of the three dummy variables for black, hispanic, and white workers in equation (A.1') are
calculated as the difference between the corresponding coefficients in equation (A.3') and the weighted average of wage levels \( \bar{WA} \) \( (-0.0374 = 1.7211 - 1.7585, -0.2223 = 1.5362 - 1.7585, \) and \( 0.0642 = 1.8227 - 1.7585) \). The coefficients for the human capital controls are again the same in equation (A.1') and equation (A.3').

Similarly, the estimated variance-covariance matrix (A.31') of the coefficients in equation (A.1') can be obtained from the variance-covariance matrix (A.38') for equation (A.3'), by applying equations (A.39)-(A.43) as follows:

\[
\text{Var}(\hat{\alpha}) = \begin{bmatrix} 0.35 & 0.10 & 0.55 \\ 0.01583 & 0.01173 & 0.01865 \\ 0.01173 & 0.01142 & 0.01437 \\ 0.01865 & 0.01437 & 0.02359 \end{bmatrix} \text{Var-Cov}(\hat{\beta}) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0.35 \\ 0.10 \\ 0.55 \end{bmatrix} = \begin{bmatrix} 0.01877 \end{bmatrix},
\]

\[
\text{Cov}(\hat{\beta}, \hat{\alpha}) = \begin{bmatrix} -0.00200 & -0.00156 & -0.00239 \\ 0.00038 & 0.00031 & 0.00040 \end{bmatrix} \begin{bmatrix} 0.35 \\ 0.10 \\ 0.55 \end{bmatrix} = \begin{bmatrix} -0.00217 \end{bmatrix},
\]

366
\[
\text{Cov}(\hat{\beta}, \hat{\alpha}) = \begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
\end{bmatrix} - \begin{bmatrix}
1 \\
0.35 & 0.10 & 0.55 \\
0.01583 & 0.01173 & 0.01865 \\
0.01173 & 0.01142 & 0.01437 \\
0.01865 & 0.01437 & 0.02359 \\
\end{bmatrix} \cdot \begin{bmatrix}
0.35 \\
0.10 \\
0.55 \\
\end{bmatrix} = \begin{bmatrix}
-0.00180 \\
-0.00562 \\
0.00217 \\
\end{bmatrix}.
\]

\[
\text{Cov}(\hat{\beta}, \hat{\beta}) = \begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
\end{bmatrix} - \begin{bmatrix}
1 \\
0.35 & 0.10 & 0.55 \\
0.00200 & 0.00038 \\
-0.00156 & 0.00031 \\
0.00017 & -0.00000 \\
0.00061 & -0.00007 \\
-0.00022 & 0.00002 \\
\end{bmatrix} \cdot \begin{bmatrix}
0.35 \\
0.10 \\
0.55 \\
\end{bmatrix} = \begin{bmatrix}
-0.00200 & 0.00038 \\
-0.00156 & 0.00031 \\
-0.00023 & 0.00040 \\
\end{bmatrix}.
\]

Again, the estimated variance-covariance sub-matrix of the coefficients for the human capital controls is the same for both equation (A.1') and equation (A.3').

The variance-covariance matrix (A.31') can be employed to establish inference procedures about model (A.1). In particular, I can derive the standard errors of the coefficients in equation (A.1'):

\[
\ln W_i = 1.7585 + 0.0557 \text{EDUC}_i + 0.0133 \text{EXP}_i - 0.0374 \text{D}_{\text{BLACK}} + 0.2223 \text{D}_{\text{HISP}} + 0.0642 \text{D}_{\text{WHITE}}.
\]

A \( t \)-test concerning each of the dummy parameters in model (A.1) has now a more straightforward and meaningful interpretation in terms of wage differentials. It tests whether the wage of black, hispanic and/or white workers is significantly different from the wage of the average worker in the whole sample. Thus equation (A.1'') shows that the wage of black workers is not significantly different from that of the average worker, the wage of hispanic
workers is significantly different from that of the average worker at the 1% level, and the wage of white workers is significantly different from that of the average worker at the 5% level, but not at the 1% level.

To summarize, models (A.1), (A.2), and (A.3) are simple alternative parameterizations of the same theoretical model and therefore share identical statistical properties (Suits, 1984). However, model (A.1) provides a more informative picture of the size and statistical significance of estimated wage differentials. Compared to model (A.2), it produces an absolute rather than relative measure of wage differentials and gives additional information on the differential for white workers, who, in model (A.2), are treated as the reference category. Compared to model (A.3), it shows directly wage differences rather than wage levels for the different ethnic groups.

Returning to the incorrect procedure adopted by Krueger and Summers (1988), we can now evaluate the consequences of their approach and the difference between the variances of the dummy coefficients from model (A.1') \((\hat{\delta}_{black}^*, \hat{\delta}_{hisp}^*)\) and the corresponding variances of the dummy coefficients from model (A.2') \((\hat{\delta}_{black}^*, \hat{\delta}_{hisp}^*)\) in this particular example. Note that since \(\hat{\delta}_{white}^*\) is not defined in model (A.2'), Krueger and Summers would ignore the wage differentials for white workers in equation (A.1''). The relationship between the variances of model (A.1') and those of model (A.2') can be illustrated as follows:

\[
\text{Var}(\hat{\delta}_{black}^*) = \text{Var}(\hat{\delta}_{black}^*) + s_{black}^2 \text{Var}(\hat{\delta}_{black}^*) - 2s_{black} \text{Var}(\hat{\delta}_{black}^*) + \\
+ s_{hisp}^2 \text{Var}(\hat{\delta}_{hisp}^*) - 2(1 - s_{black})s_{hisp} \text{Cov}(\hat{\delta}_{black}^*, \hat{\delta}_{hisp}^*)
\]

\[
= 0.00211 + 0.35^2(0.00211) - 2(0.35)(0.00211) + \\
+ 0.10^2(0.00626) - 2(1 - 0.35)(0.10)(0.00229)
\]

\[= 0.00066.
\]
\[ \begin{align*} 
\text{Var}(\hat{\delta}_\text{HISP}) &= \text{Var}(\hat{\delta}_\text{HISP}) + s^2_{\text{HISP}} \text{Var}(\hat{\delta}_\text{HISP}) - 2s_{\text{HISP}} \text{Var}(\hat{\delta}_\text{HISP}) + \\
&+ s^2_{\text{BLACK}} \text{Var}(\hat{\delta}_\text{BLACK}) - 2s_{\text{BLACK}}(1 - s_{\text{HISP}}) \text{Cov}(\hat{\delta}_\text{HISP}, \hat{\delta}_\text{BLACK}) \\
&= 0.00626 + 0.102(0.00626) - 2(0.10)(0.00626) + \\
&+ 0.35^2(0.00211) - 2(0.35)(1 - 0.10)(0.00229) \\
&= 0.00389. 
\end{align*} \]

The differences between \(\text{Var}(\hat{\delta}_\text{BLACK})\) and \(\text{Var}(\hat{\delta}_\text{BLACK})\) and between \(\text{Var}(\hat{\delta}_\text{HISP})\) and \(\text{Var}(\hat{\delta}_\text{HISP})\) would be smaller, the smaller the (absolute) values of \(\text{Var}(\hat{\delta}_\text{BLACK}), \text{Var}(\hat{\delta}_\text{HISP})\).

\(\text{Cov}(\hat{\delta}_\text{BLACK}, \hat{\delta}_\text{HISP})\) and/or the smaller the values of \(s_{\text{BLACK}}\) and \(s_{\text{HISP}}\). If \(s_{\text{BLACK}}\) and \(s_{\text{HISP}}\) were close to zero, all the terms after the first in both equations would tend to vanish, so that \(\text{Var}(\hat{\delta}_\text{BLACK})\) would approach \(\text{Var}(\hat{\delta}_\text{BLACK})\) and \(\text{Var}(\hat{\delta}_\text{HISP})\) would approach \(\text{Var}(\hat{\delta}_\text{HISP})\).

Given the relative magnitudes of \(\text{Var}(\hat{\delta}_\text{BLACK}), \text{Var}(\hat{\delta}_\text{HISP})\) and \(\text{Cov}(\hat{\delta}_\text{BLACK}, \hat{\delta}_\text{HISP})\), the sign of \(\text{Cov}(\hat{\delta}_\text{BLACK}, \hat{\delta}_\text{HISP})\) (positive), and the relative magnitudes of \(s_{\text{BLACK}}\) and \(s_{\text{HISP}}\) in this example, \(\text{Var}(\hat{\delta}_\text{BLACK})\) is smaller than \(\text{Var}(\hat{\delta}_\text{HISP})\) and \(\text{Var}(\hat{\delta}_\text{HISP})\) is smaller than \(\text{Var}(\hat{\delta}_\text{HISP})\). However, since variances and covariance are rather small, the differences are only of order \(10^{-3}\). Despite these very small differences, the use of \(\text{SE}(\hat{\delta}_\text{BLACK})\) and \(\text{SE}(\hat{\delta}_\text{HISP})\) instead of \(\text{SE}(\hat{\delta}_\text{BLACK})\) and \(\text{SE}(\hat{\delta}_\text{HISP})\), à la Krueger and Summers, would change our evaluations about the statistical significance of the individual dummy parameters in model (A.1). The wage differential of black workers would remain not statistically significant, but the wage differential of hispanic workers would become statistically significant only at the 5% level, and the wage differential of white workers would be completely ignored.

We can also evaluate the difference between the variances of the dummy coefficients from model (A.1') \(\text{Var}(\hat{\delta}_\text{BLACK}), \text{Var}(\hat{\delta}_\text{HISP}), \text{Var}(\hat{\delta}_\text{WHITE})\) and the corresponding variances of the dummy coefficients from model (A.3') \(\text{Var}(\hat{\delta}_\text{BLACK}), \text{Var}(\hat{\delta}_\text{HISP}), \text{Var}(\hat{\delta}_\text{WHITE})\) in this
example. The relationships between the variances of model (A.1') and those of model (A.3') are shown below:

\[
\text{Var}(\delta_{\text{BLACK}}) = \text{Var}(\delta_{\text{BLACK}}^*) + s_{\text{BLACK}}^2 \text{Var}(\delta_{\text{BLACK}}^*) - 2s_{\text{BLACK}} \text{Var}(\delta_{\text{BLACK}}^*) + \\
+ s_{\text{HISP}}^2 \text{Var}(\delta_{\text{HISP}}^*) + s_{\text{WHITE}}^2 \text{Var}(\delta_{\text{WHITE}}^*) - \\
- 2(1 - s_{\text{BLACK}})s_{\text{HISP}} \text{Cov}(\delta_{\text{BLACK}}^*, \delta_{\text{HISP}}^*) - \\
- 2(1 - s_{\text{BLACK}})s_{\text{WHITE}} \text{Cov}(\delta_{\text{BLACK}}^*, \delta_{\text{WHITE}}^*) + \\
+ 2s_{\text{HISP}}s_{\text{WHITE}} \text{Cov}(\delta_{\text{HISP}}^*, \delta_{\text{WHITE}}^*)
\]

\[
= 0.01583 + 0.35^2(0.01583) - 2(0.35)(0.01583) + \\
+ 0.10^2(0.01142) + 0.55^2(0.02359) - \\
- 2(1 - 0.35)(0.10)(0.01173) - \\
- 2(1 - 0.35)(0.55)(0.01865) + \\
+ 2(0.10)(0.55)(0.01437)
\]

\[
= 0.00066,
\]

\[
\text{Var}(\delta_{\text{HISP}}) = \text{Var}(\delta_{\text{HISP}}^*) + s_{\text{HISP}}^2 \text{Var}(\delta_{\text{HISP}}^*) - 2s_{\text{HISP}} \text{Var}(\delta_{\text{HISP}}^*) + \\
+ s_{\text{BLACK}}^2 \text{Var}(\delta_{\text{BLACK}}^*) + s_{\text{WHITE}}^2 \text{Var}(\delta_{\text{WHITE}}^*) - \\
- 2s_{\text{BLACK}}(1 - s_{\text{HISP}}) \text{Cov}(\delta_{\text{BLACK}}^*, \delta_{\text{HISP}}^*) - \\
- 2(1 - s_{\text{HISP}})s_{\text{WHITE}} \text{Cov}(\delta_{\text{HISP}}^*, \delta_{\text{WHITE}}^*) + \\
+ 2s_{\text{BLACK}}s_{\text{WHITE}} \text{Cov}(\delta_{\text{BLACK}}^*, \delta_{\text{WHITE}}^*)
\]

\[
= 0.01142 + 0.10^2(0.01142) - 2(0.10)(0.01142) + \\
+ 0.35^2(0.01583) + 0.55^2(0.02359) - \\
- 2(0.35)(1 - 0.10)(0.01173) - \\
- 2(1 - 0.10)(0.55)(0.01437) + \\
+ 2(0.35)(0.55)(0.01865)
\]

\[
= 0.00389,
\]
\[ Var(\delta_{\text{WHITE}}) = Var(\delta_{\text{WHITE}}^*) + s^2_{\text{WHITE}} Var(\delta_{\text{WHITE}}^*) - 2s_{\text{WHITE}} Var(\delta_{\text{WHITE}}^*) + \]
\[ + s^2_{\text{BLACK}} Var(\delta_{\text{BLACK}}^*) + s^2_{\text{HISP}} Var(\delta_{\text{HISP}}^*) - \]
\[ - 2s_{\text{BLACK}} (1 - s_{\text{WHITE}}) \text{Cov}(\delta_{\text{BLACK}}^*, \delta_{\text{WHITE}}^*) - \]
\[ - 2s_{\text{HISP}} (1 - s_{\text{WHITE}}) \text{Cov}(\delta_{\text{HISP}}^*, \delta_{\text{WHITE}}^*) + \]
\[ + 2s_{\text{BLACK}} s_{\text{HISP}} \text{Cov}(\delta_{\text{BLACK}}^*, \delta_{\text{HISP}}^*) \]
\[ = 0.02359 + 0.55^2(0.02359) - 2(0.55)(0.02359) + \]
\[ + 0.35^2(0.01583) + 0.10^2(0.01142) - \]
\[ - 2(0.35)(1 - 0.55)(0.01865) - \]
\[ - 2(0.10)(1 - 0.55)(0.01437) + \]
\[ + 2(0.35)(0.10)(0.01173) \]
\[ = 0.00048 . \]

The differences between \( Var(\delta_{\text{BLACK}}^*) \) and \( Var(\delta_{\text{BLACK}}^*) \), between \( Var(\delta_{\text{HISP}}^*) \) and \( Var(\delta_{\text{HISP}}^*) \), and between \( Var(\delta_{\text{WHITE}}^*) \) and \( Var(\delta_{\text{WHITE}}^*) \) would be smaller, the smaller the (absolute) values of \( Var(\delta_{\text{BLACK}}^*) \), \( Var(\delta_{\text{HISP}}^*) \), \( Var(\delta_{\text{WHITE}}^*) \), \( \text{Cov}(\delta_{\text{BLACK}}^*, \delta_{\text{HISP}}^*) \), \( \text{Cov}(\delta_{\text{BLACK}}^*, \delta_{\text{WHITE}}^*) \), and/or the smaller the values of \( s_{\text{BLACK}} \), \( s_{\text{HISP}} \), \( s_{\text{WHITE}} \). If \( s_{\text{BLACK}} \), \( s_{\text{HISP}} \) and \( s_{\text{WHITE}} \) were close to zero, all the terms after the first in the three equations would tend to vanish, so that \( Var(\delta_{\text{BLACK}}^*) \) would approach \( Var(\delta_{\text{BLACK}}^*) \), \( Var(\delta_{\text{HISP}}^*) \) would approach \( Var(\delta_{\text{HISP}}^*) \), and \( Var(\delta_{\text{WHITE}}^*) \) would approach \( Var(\delta_{\text{WHITE}}^*) \).

A.6 Conclusions

In this general Appendix I have illustrated the relationship between alternative specifications of a dummy variable model. In particular, I have presented the simple matrix algebra formulae which are necessary to reconstruct the general specification of the model (A.1) from one of the two specific models (A.2) and (A.3). Model (A.1) is not directly estimable by OLS due to the dummy trap problem, however it represents a parameterization which is of special interest in economic terms. In large models with many different sets of
dummy variables, the economic interpretation of the dummy coefficients in equations like (A.2) and (A.3) can be quite difficult, while model (A.1) always provides particularly straightforward and useful results.
## Appendix: Data Used for the Numerical Example

### Individual wages and human capital/demographic characteristics

<table>
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<th>i</th>
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<th>ln(W/H)</th>
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<th>EXP</th>
<th>D_BLACK</th>
<th>D_HISP</th>
<th>D_WHITE</th>
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<td>2.35</td>
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<td>0.51</td>
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*Source:* Data created by the author, with (some) reference to the United States labour market.

*Notes:* The variables are defined as follows:

- **W/H** = average hourly wage
- **ln(W/H)** = logarithm of the average hourly wage
- **EDUC** = years of schooling
- **EXP** = years of experience in the labour market
- **D_BLACK** = dummy variable for ethnicity; equal to 1 for black individuals
- **D_HISP** = dummy variable for ethnicity; equal to 1 for hispanic individuals
- **D_WHITE** = dummy variable for ethnicity; equal to 1 for white individuals.
References


