EUI Working Papers

MWP 2011/13
MAX WEBER PROGRAMME

SOCIAL CLASS, EMPLOYMENT CONTRACTS AND ECONOMIC SECURITY IN THE RUSSIAN LABOUR MARKET

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EUI Working Paper **MWP** 2011/13

ISSN 1830-7728

Printed in Italy
European University Institute
Badia Fiesolana
I – 50014 San Domenico di Fiesole (FI)
Italy
www.eui.eu
cadmus.eui.eu

Abstract

In this paper I explore occupational class differences in employment contracts, fringe benefits and unemployment risks in Russia. Using panel data, I provide both a descriptive account of class differentials in these labour market outcomes and fixed-effects estimates of the effects of occupational class. I also discuss the dynamics of the class structure in post-Soviet Russia.

Keywords

Occupational class, ESeC, employment contracts, Russia.

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Max Weber Fellow, 2010-2011

1 Validation of the EGP and ESeC class schemes

The operationalization of the Erikson-Goldthorpe (EGP) occupational class schema is based on the expert allocation of occupations (given employment and supervisory status) to classes. A natural question is to what extent this operationalization corresponds to the theoretical foundations of the EGP schema, or, in other words, whether the schema measures what it is supposed to measure. Several studies conducted in the last twenty years tested the validity of the EGP class schema and, recently, the European Socio-Economic Classification (ESeC).

Researchers usually differentiate between construct and criterion validity. To test the construct validity of a measure a check needs to be made of whether the measure predicts factors that it is theoretically expected to predict. For example, we expect that classes have different political preferences or mortality risks. If the measure of class is not associated with these factors, it is likely to be erroneous. On the other hand, it is also possible that there is truly no association between these variables in some particular social contexts.

Criterion validity tests whether the measure of a concept is similar to other possible measures of the same concept. For class, the test would be to compare the usual operationalization based on the allocation of occupations to classes with a classification based on the directly observed employment contracts.

In the first attempt to validate the EGP class schema, Evans (1992) tested both construct and criterion validity of the schema, using the 1984 Social Class in Modern Britain survey. He compared EGP classes in terms of chances for promotion, being on a recognized career ladder, opportunities for on-the-job training, regular pay increments, forms of payment (productivity payment vs. salary) and work autonomy. The selection of these variables was informed by Goldthorpe's class theory. For Goldthorpe, class-related differences in employment contracts stem from the differences in skills specificity and work monitoring across occupations. If a job requires longer training and highly specific skills and the direct monitoring and control is difficult, employers have incentives to offer employees the service contract that includes being on a career ladder, being paid a salary rather than some form of productivity payment, and greater work autonomy.

On the other hand, if work monitoring is easy, long training is not required and workers can be easily replaced, employers offer labour contracts with productivity payment, low career prospects and low work autonomy. The service contract is typical for non-manual occupations while the labour contract usually applies for manual occupations. For some occupations, a mixed form of the contract is characteristic, combining features of both service and labour contracts (Goldthorpe, 2007).

If the theory is correct, we would expect that EGP classes differ in respect to the validation variables that directly measure class-related elements of employment contracts. Indeed, Evans (1992) concluded that the analysis identified clear distinctions between the salariat (managers and professionals), the working class and the intermediate classes. On the other hand, there were not many differences between classes I and II within the salariat (higher managers and professionals vs. lower managers and professionals), and between skilled and unskilled manual workers.

Using the same data set, Birkelund et al. (1996) for the first time applied latent structure analysis in order to identify the latent variables for employment contracts and to classify respondents into the latent classes. Both for men and women, observed variables that measure different elements of employment contracts could be grouped into three latent dimensions: payment conditions, promotion prospects and job autonomy. For each of those dimensions, Birkelund et al. (1996) classified respondents into several latent classes (from two to four), focusing on the differences between men and women, though they did not attempt to validate the EGP schema directly.

Evans and Mills (1998) applied latent class analysis to classify respondents into classes jointly for men and women, on the basis of nine variables related to payment conditions, career prospects and job autonomy (with the same data set as in two previous studies). They identified four latent classes that broadly correspond to the classes in the EGP schema. Two of those latent classes represented the salariat and the working class, and the third latent class was close to manual supervisors and technicians. However, the routine non-manual class could not be identified as a distinctive group in the latent class solution. Furthermore, as in the previous studies, skilled and unskilled workers could not be separated on the basis of the characteristics of their employment contracts.

Evans and Mills (2000) conducted a similar analysis with the new data from a 1996 ONS survey. With this data set, the best latent class solution contained three classes that corresponded to the salariat, the intermediate class and the working class employment contracts. The latent classes generally fit the EGP schema. However, the line between the service and intermediate contracts run within class 2 (lower managers and professionals), suggesting a smaller salariat compared to the usual operationalization of the EGP class.

Furthermore, Evans and Mills (2000) examined possible differences between the employment contracts of managers and professionals. They did not find significant differences in the class-related characteristics of these two groups. This finding was later confirmed by Mills in McGovern et al. (2007).

The validity of the National Statistics Socio-Economic Classification (NS-SEC), the class schema that inherited all the major characteristics of the old EGP schema, but suggested a somewhat different coding routine, was tested and confirmed in Rose et al. (2003).

Goldthorpe and McKnight (2006) compared NS-SEC classes with respect to economic security, stability and prospects, operationalized as unemployment risks, forms of payment and the shape of age-earnings profiles. They found a clear class gradient in the unemployment risks, with the salariat having the lowest unemployment risks and the working class the highest unemployment risks. The working class also had a higher proportion of productivity payment (bonuses, piecework, profit-related commissions) and overtime pay in total earnings (compared to the salariat and the intermediate class). The salariat had the steepest cross-sectional age-earnings profiles, while the profiles for the working classes were rather flat. In other words, the earnings of working class men were similar for men of different ages, while older members of the salariat earned more than their younger colleagues demonstrating that there are better chances for promotion in the salariat.

The ESeC schema that has been constructed on the basis of the EGP and NS-SEC schemes and was designed for cross-national research, was extensively validated recently with the data from the UK, Germany, Sweden, Italy and some other mainly Western European countries, both for criterion and construct validity (Rose and Harrison, 2010). The studies published in this volume show that ESeC is correlated with measures of job autonomy, career prospects and indicators of piece-wise and time-related compensation. There are also differences across ESeC classes in risks of poverty and deprivation, unemployment risks, patterns of wage growth and subjective health.

Most of the analysis that validated the EGP and related class schemes was conducted with the British data (and for the ESeC the data from some mainly Western European countries). The validation of these class schemas for Eastern European countries (not to mention other parts of the world) remain rare. Evans and Mills (1999) applied the same validation strategy as in Evans and Mills (1998) to the data from Poland and Hungary. In both countries the latent class analysis of job characteristics identified the salariat and the working class, but there was more cross-national variation in the composition of the intermediate class. It was especially hard to separate farmers (a significant proportion of the population in both countries) and other self-employed.

Some recent research shows that ESeC can be satisfactorily applied in Eastern Europe (for discussion see Rose and Harrison, 2010, p.272), but the evidence remains quite fragmentary.

The unpublished paper by Evans and Whitefield (2003) contains the only attempt to validate the EGP class for Russia. Using a number of surveys conducted between 1993 and 2001, Evans and Whitefield (2003) compared EGP classes in Russia with respect to forms of payment, work autonomy and employment prospects. The results were in the theoretically predicted direction and did not substantially differ from similar validation exercises conducted in Britain. This confirmed that EGP class could be meaningfully applied for Russia. Moreover, Evans and Whitefield (2003) found that clear differences between classes already existed in 1993 that suggests that the theoretical logic of Goldthorpe's class schema also applies to socialist economies.

EGP and ESeC class schemas are not the only approach to constructing categorical occupational classifications (see, for example, Esping-Andersen (1992), Oesch (2006), Guveli et al. (2007)). However, in this paper I focus on ESeC.

2 Validation strategy

The validation strategy that I apply in this paper differs from Evans and Whitefield (2003) in several respects. First, I explore class effects with another set of outcome variables that mainly measure economic security. Second, to validate the EGP class schema Evans and Whitefield (2003) only used bivariate associations of class with validation variables. I add individual- and firm-level controls, and also take advantage of the longitudinal character of the data set that allows a closer estimation of the causal effects of class. Third, I apply the new ESeC rather than the EGP class schema.

Perhaps the most satisfying research design for the validation of the ESeC in Russia would be to test criterion-related validity of the schema, as in Evans and Mills (1998, 1999). To do this, it would be necessary to collect data on class-related aspects of respondent's employment contracts, explore the data with latent class analysis and then compare latent classes with the ESeC. Unfortunately, the RLMS does not include questions on the type of payment and work autonomy. However, there are other variables that were previously shown to be related to occupational social class in Britain.

In order to explore the relevance of the ESeC schema to the labour market outcomes in post-Soviet Russia, I apply a strategy that is similar to Goldthorpe and McKnight (2006). I focus on three outcome variables that are all related to different aspects of economic security. These variables are the type of employment contract (formal vs. informal), the number of fringe benefits and the unemployment risks. In this section I show how all three variables are related to Goldthorpe's class theory.

Informal employment contracts are defined as a situation when an employer does not sign a formal agreement with an employee, but instead the two sides make a verbal informal agreement. When the employment contract is informal, the relationship between the employer and employee is likely to be less stable. Employers often use informal contracts when they need to attract the labour force for a short term and want to be able to dismiss workers easily when they are not needed, without going through the long administrative procedures specified in the Russian Labour Code. Although formally this is a violation of the Labour Code, verbal employment agreements are widely used in Russia and are becoming more popular (see section 6).

We can expect that in the case of the service employment contract, as defined by Goldthorpe, employers are more interested in the long-term relationship with employees. Therefore, it is less likely that they will be using short-term informal agreements. The theory predicts that the salariat will have lower risks of informal employment compared to the working class, while the intermediate classes will be somewhere in between.

The second outcome variable is the number of fringe benefits people have in their jobs, i.e. the benefits that firms provide to their workers, such as paid annual vacations, paid sick leave, free or partially paid facilities for children, etc. The logic that relates this to Goldthorpe's class theory is the same as in the case of informal contracts. If a firm is interested in long-term relationships with employees, it will provide more non-monetary benefits. Therefore, we can expect that the salariat enjoys more fringe benefits than the working class.

The third outcome variable is unemployment risks. Goldthorpe and McKnight (2006) showed that in Britain manual classes have higher unemployment risks compared to the salariat. This is related to the theory that predicts higher job security for classes with a service contract (as employers are less likely to fire workers who can be difficult to replace). I test if the theory holds in Russia.

3 Data and measures

The data come from the pooled RLMS sample for 1994-2006. The outcome variables were measured as follows.

- *Informal contracts.*

The RLMS asked the following question: "Tell me, please: are you employed in this job officially, in other words, by labour book, labour agreement, or contract?", with the possible answers "working officially" or "not officially". Additionally, in the next question the RLMS clarified the reason for not working officially. The question was "Why are you not officially employed?", with two possible answers: "Employer did not want this" or "I did not want this".

These questions were available only in the years 1998, 2000, 2002, 2003 to 2006 and were asked only of the people who stated that they worked in an enterprise or organization. 8% of respondents in 2006 said that they did not work in enterprises and organizations. These are the self-employed and employees working for the self-employed. The type of employment contract for them is unknown, although it is most likely that verbal employment agreements among them are more widespread. These people were excluded from the analytic sample. Unemployed and people out of the labour force also were excluded. I used the data on the type of contract in primary jobs only; secondary employment has not been taken into account.

- *Fringe benefits.*

Fringe benefits were measured according to the scale constructed from the following RLMS question:

"Are you given the following fringe benefits in this job:

1. Regular paid vacations.

2. Paid sick leave.

3. Paid leave for pregnancy, giving birth, and caring for a child until the age of 3.

4. Free treatment in a departmental medical institute, full or partial payment for treatment in other medical institutes.

5. Full or partial payment for sanitarium, children's camps, or tourist camps.

6. Free child care in a departmental preschool, full or partial payment for child care in another preschool.

7. Free or discounted food or payment for food.

8. Grants for travel, payment for travel passes.

9. Education paid for by the organization.

10. Granting of loans, credit for house building or repair, discounts on building supplies

11. Subsidized rent for housing".

All questions could be answered either "yes" or "no".

These questions were available for the years 2000 to 2006 and were asked only of the people who worked in enterprises and organizations (i.e., were not self-employed and did not work for the self-employed).

- *Unemployment risks.*

To measure unemployment risks I create a dummy variable equal to one if the person is unemployed in the next RLMS round. Unemployment is defined as being not employed and looking for a job.

In regression models with these three outcome variables I use the same set of predictors described below.

- *Class.*

The main variable of interest is occupational social class as operationalized in the ESeC schema. As previously discussed, managers and professionals were separated. As in Gerber and Hout (2004), I distinguish managers (both higher and lower) from higher professionals and lower professionals. This allows us to test empirically if managers and professionals are indeed different in terms of their employment contracts.

The following variables are used as controls.

The individual-level controls are:

- *Gender.*

The analysis was conducted jointly for men and women, with a control for gender. Therefore, class effects represent weighted averaged effects for men and women.

- *Age and age squared.* Age squared was added as the relationship between the outcome variables and class is curvilinear.

In most models, education was not controlled, for the reasons explained in the next section.

The firm-level variables were coded with the information that respondents provided about their jobs.

- *Sector of economy* (public or private). I coded a firm as belonging to the public sector if respondents claimed that there were no private firms or individuals among the owners of this firm. Therefore, all firms with mixed public-private ownership were coded in the private sector.

- *Firm size* coded at three levels: small enterprises (less than 50 employees), large enterprises (50 and more employees), no information (many people in the survey did not answer the question about the number of people working in their enterprises).

- *Location:* a big city, a town or the countryside.

Two more firm-level controls were available only for some years in the RLMS. These are:

- *Branch of the economy*: industry, construction, trade and services, agriculture, public services (health, education, culture, police, army, state administration), transport and communications, others. This variable is available for the years from 2004 to 2006.

- Year of the foundation of the firm. Clarke and Kabalina (2000) specified the differences between the new private sector (new firms that were founded after the collapse of the USSR) and old Soviet privatized enterprises. Unfortunately, the RLMS has a variable for the year of the foundation of the firm only for the years from 1994 to 2002. Then the question was dropped from the survey, most likely because of the high non-response rate. I group the firms into those that were founded before 1992, in 1992 and later, and those for which the information was not available.

All the models for informal contracts and fringe benefits were estimated with the sample of the respondents who were employed in firms and organizations. The self-employed and those who worked for the self-employed were excluded. The analysis for unemployment risks was based on the sample that included all employed people. The size of analytic samples differed and is reported separately for each model in the sections that follow.

4 Modelling strategy

The statistical models presented in this paper have two purposes. First, I describe the associations between class and three outcome variables, with and without a number of control variables. Second, I estimate the average effect of changing class for the same individuals, thus controlling for unobserved individual heterogeneity.

As the RLMS is a household panel survey, for most of the individuals in the sample we have repeated observations for several years. I pool the data for all rounds and estimate the models with the pooled sample, adding dummy variables for each year. Thus, I estimate the average effect of class for the years 1994 to 2006.

The residuals for observations for the same individuals in different rounds are likely to be correlated, and as a consequence of that, ordinary regression can produce biased standard errors for coefficients. To solve this problem, I use regression models with random effects. These models are similar to ordinary regression, but instead of one intercept that is common for all individuals I fit a specific intercept for each individual. For an individual j in round i the outcome y_{ji} is a linear combination of the intercept a_j, the sum of products of predictors and their parameters β_{ij} and the error ϵ_{ij}. The individual intercepts are modelled to follow the normal distribution with the mean equal to zero (Gelman and Hill, 2007; Rabe-Hesketh and Skrondal, 2008).

$$y_{ij} = \alpha_j + \beta_{ij} + \epsilon_{ij}$$
$$\alpha_j \sim \mathrm{N}(0, \sigma^2)$$

These equations apply to the models with interval dependent variables. For binary dependent variables, I use the logit link function instead of the identity link function. In this paper, fringe benefits were measures on a continuous scale, while being on informal contract and being unemployed are binary variables.

The random-effects model does not give reliable estimates of standard errors when the number of observations per cluster (i.e., the number of rounds per individual) is fewer than three. In this case, I estimate standard errors with the robust variance matrix, adjusted for the correlation of residuals for the same individuals, as programmed in Stata option `cluster` (Wooldridge, 2003).

Class was entered into models as a set of dummy variables, with routine workers as the reference category.

The logic of the models presented so far is rather descriptive. I analyze whether classes are different in respect to three outcome variables, when two individual-level controls (age and gender) and some firm-level characteristics are taken into account. I do not control for education because of a high correlation between class and education and the difficulties with the interpretation of the results of this model. This strategy does not estimate the causal effects of class as the coefficients can be affected by other unobserved factors outside the estimated model that are correlated with class.

It is well known that causality is hard to demonstrate statistically with observational data. However, longitudinal data allow us to come closer to the estimation of the causal effects of class. To do this, I estimate fixed-effects models that control for time-constant individual heterogeneity. In other words, I add to the model estimated with the pool panel data set a set of dummies for individuals. Therefore, the model estimates the effects of class and other time-varying variables within individuals, excluding the possibility that the coefficients for class can be biased by some time-constant individual characteristics associated with class (for example, stronger preference for informal contracts among people who become manual workers).

The difference with the random-effects approach is that the individual intercepts are not modelled, but are entered as fixed parameters for each individual.

$$y_{ij} = \alpha_j + \beta_{ij} + \epsilon_{ij}, \tag{1}$$

where a_j are parameters for dummy variables for each person in the sample.

With the fixed-effects models, we can only estimate the effects of time-varying variables. Also note that the sample includes only those individuals, for whom the dependent variable changed during the period of observation. In some cases, this severely restricts the sample. Less than 800 out of 11,000 thousand people in our sample experienced both formal and informal employment. It is unlikely that they represent just a random sub-sample. This definitely limits the extent as to how the results of fixed-effects estimation might be generalized to the population at large.

The number of people who were both employed and unemployed at different points of time is even smaller. In effect, fixed-effects estimation for this variable does not produce meaningful results and I do not present it in this paper.

Finally, fixed-effects regressions do not account for time-varying omitted variables that can still bias the parameters for class. An example for such a variable would be health.

The equation 1 presents the model for interval dependent variables. When the outcome variable is binary, I use the conditional logit model that is equivalent to fixed-effects models (Rabe-Hesketh and Skrondal, 2008).

To construct a scale for fringe benefits with the set of binary variables I use the summated rating model (SRT) and Mokken scaling. The details are given in section 7.

Before proceeding to the presentation of the results of regression analysis, I show and discuss the descriptive statistics for the class structure in post-Soviet Russia.

5 The class structure in post-Soviet Russia

Table 1 shows changes in the class structure in Russia from 1994 to 2006, separately for men and women. The same information is graphically displayed in Figures 1 and 2.

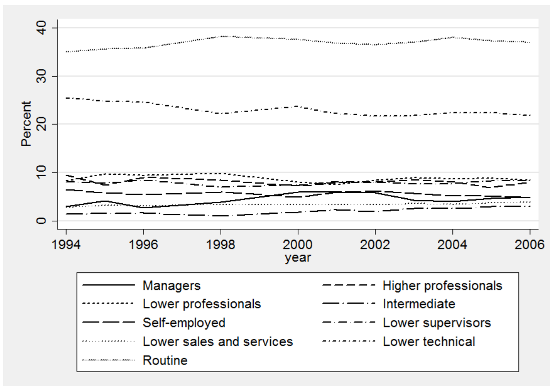

Figure 1: The class structure in Russia, men, 1994-2006. The data for 1997 and 1999 are missing.

Several conclusions can be made. Compared with Western countries, there is a higher proportion of manual workers, especially among men. In 2006, 37% of employed Russian men were routine (non-skilled) manual workers, and 22% were lower technical (skilled) manual workers. There were relatively few managers, self-employed and professionals. (The comparison with Western countries is based on the data in Rose and Harrison (2010)).

For women, the proportion of manual workers is somewhat lower than for men. The largest class is lower professionals (this includes such occupa-

Table 1: The class structure in Russia, 1994-2006[a]

ESeC	1994	1995	1996	1998	2000	2001	2002	2003	2004	2005	2006
Men (%)											
1a/2a.Managers	2.9	4.1	2.7	3.9	5.9	5.9	5.8	4.3	4.0	4.6	4.9
1b.Higher professionals	9.5	7.4	9.0	8.4	7.2	7.9	8.0	8.5	8.1	6.9	8.0
2b.Lower professionals	8.3	9.7	9.4	9.8	8.0	7.5	8.4	8.9	8.7	8.8	8.4
3.Intermediate	1.4	1.5	1.6	1.0	1.8	2.3	1.9	2.6	2.5	2.9	2.9
4/5.Self-employed	6.5	5.8	5.4	6.0	4.9	5.9	6.2	5.7	5.2	5.1	4.8
6.Lower supervisors and technicians	8.1	7.8	8.5	7.0	7.4	8.1	8.1	7.6	7.7	8.3	8.3
7.Lower sales and services	2.8	3.2	3.1	3.4	3.4	3.4	3.3	3.6	3.4	3.7	3.9
8.Lower technical	25.5	24.8	24.6	22.2	23.7	22.2	21.7	21.8	22.4	22.4	21.8
9.Routine	35.0	35.6	35.8	38.2	37.6	36.8	36.5	37.0	38.0	37.3	37.0
Women (%)											
1a/2a.Managers	1.6	2.9	2.0	3.0	4.0	5.2	4.8	2.6	2.8	3.2	3.2
1b.Higher professionals	13.0	12.7	13.5	13.4	12.0	13.2	11.9	12.9	12.7	11.1	11.7
2b.Lower professionals	25.4	24.5	25.8	24.8	24.5	22.0	23.2	22.5	22.4	22.8	24.3
3.Intermediate	9.7	10.0	9.1	9.7	10.4	11.6	12.1	11.0	12.2	12.4	11.4
4/5.Self-employed	2.8	2.8	3.7	3.3	3.6	3.8	3.5	4.2	3.6	3.3	3.0
6.Lower supervisors and technicians	7.1	5.7	6.0	4.8	4.7	4.6	4.5	4.9	4.7	4.6	5.2
7.Lower sales and services	12.3	13.6	12.3	15.3	16.2	14.8	14.8	16.3	16.3	17.8	17.1
8.Lower technical	5.9	4.8	4.8	4.0	4.0	3.5	4.0	3.7	4.1	4.4	4.5
9.Routine	22.3	23.1	22.7	21.6	20.5	21.4	21.1	22.0	21.1	20.3	19.5

[a] Data source: RLMS 1994-2006.

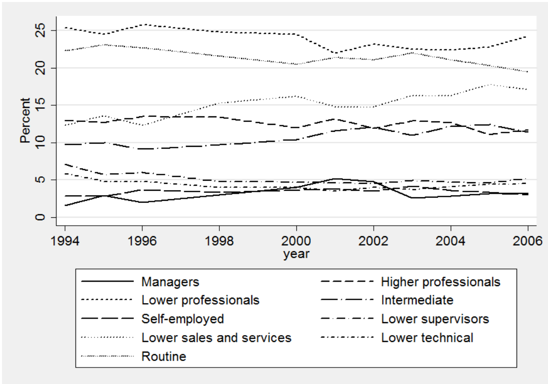

Figure 2: The class structure in Russia, women, 1994-2006. The data for 1997 and 1999 are missing.

tions as nursing and secondary school teaching). The next classes by their size are routine workers and lower sales and services workers (mainly salespersons and cashiers). There are only a few lower technical workers among women. The intermediate class (bookkeepers, secretaries, etc.) and the class of higher professionals are both larger for women than for men, while there are more male managers and self-employed.

The Russian class structure did not change significantly between 1994 and 2006. Among men, the number of lower technical industrial workers slightly decreased, while the number of routine and lower sales and service workers and managers somewhat increased. Similar developments can be observed for women, for whom the biggest increase was in the lower sales and service class. These changes reflect the industrial crisis in post-Soviet Russia and the development of the service sector. Overall, the changes were not dramatic and the distribution of the labour force across classes remained relatively stable. The longer time-series for the class structure that started in the 1980s (Bian and Gerber, 2008) showed a more substantial decrease in the proportion of industrial workers, but most of this reduction happened before 1994.

6 Class and informal employment contracts

Informal employment contracts became more widespread in Russia in the 2000s, although formally they are a violation of Russian labour legislation. According to the RLMS data, in 2006 7% of employees in firms and organizations had verbal employment agreements. Employers benefit from informal contracts as they can avoid paying taxes, do not have to comply with the requirements of the Labour Code and can be more flexible in the regulation of the size of the labour force. Violations of the Labour Code are rarely prosecuted.

Informal employment in Russia was studied by a number of Russian labour economists and sociologists (Gimpelson, 2004; Gimpelson and Kapelyushnikov, 2006; Sinyavskaya, 2005; Barsukova, 2003). They used both official statistics and survey data, including the RLMS. It was shown that informal employment is more widespread among the youngest and the oldest workers, the least educated workers, in the private sector of economy, in small enterprises and in some branches of the economy, such as construction and trade. However, the determinants of informal employment were not studied with the methods of multivariate statistics. Nor was occupational social class ever used as a predictor of informal employment.

Figure 3 shows the change in the percentage of workers who had informal employment contracts from 1998 to 2006.[1] In 1998 only 2% of people employed in organizations had informal contracts. By 2006 this percent rose to 7%.

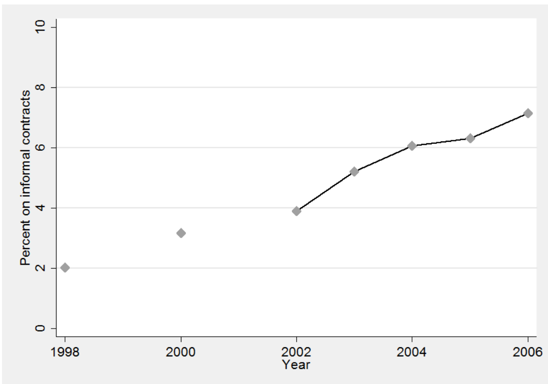

Figure 3: Percent of informally employed, 1998-2006. The data for 1999 and 2001 are missing.

Figure 4 shows the distribution of informal contracts across ESeC classes in the pooled RLMS sample for 1998-2006. The labour contract classes (lower sales and services, lower technical and routine) have the highest per-

[1]All the percentages in this paper were calculated with the analytical sample that excludes the self-employed and those who work for the self-employed.

centage of informally employed. The service relationship classes (managers and professionals) have the lowest percentage of informally employed, while "mixed" contract classes (intermediate and lower supervisors) are somewhere in the middle. The aim of the multivariate analysis that follows below is to check if this association holds after introducing controls.

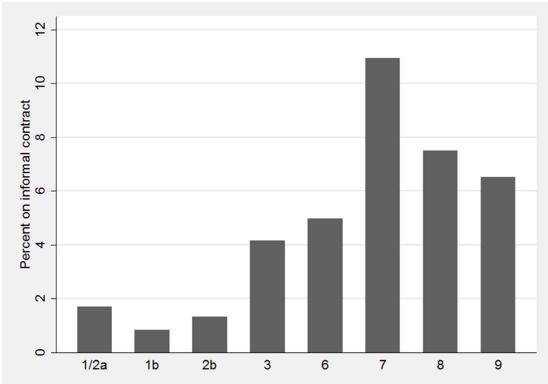

Figure 4: Distribution of informally employed across ESeC classes, 1998-2006. 1/2a - managers, 1b - higher professionals, 2b - lower professionals, 3 - intermediate, 6 - lower supervisors and technicians, 7 - lower sales and services, 8 - lower technical, 9 - routine.

Table 2 shows the results of several logit models that predict the probability of having an informal employment contract. Model (1) fits a regression with two predictors: class and dummies for years. This is another way to present descriptive statistics shown in Figure 4. Model (2) controls for sex, age, firm characteristics and location.

Class effects remain largely similar to those presented in model (1). Note, however, that the difference in the probability of informal contracts between the routine and lower sales and services class reduces after controlling for firm characteristics (the size and sector). The same refers to the contrasts between routine and lower technical workers, and routine workers and lower professionals.

Control variables are associated with the probability of informal employment in the expected way. Men have a higher probability of informal contracts than women. The relation between age and probability of informal contract is concave. Employees in the state sector and large enterprises are less often employed informally. Those who live in big cities are more susceptible to informal employment compared to people living in towns and in the countryside.

The branch of the economy and the year of the foundation of the firm are available only in some rounds of the RLMS. They are added in models (3) and (4). As expected, both variables are significant predictors of informal employment. Informal employment is more widespread in construction, trade and services and in the new firms that were founded in the post-Soviet period. Although it is hard to compare logistic regression coefficients estimated with different samples (Mood, 2010), the pattern of class effects remains the same in models (3) and (4). Note that lower sales and service workers stop being significantly different from routine and lower technical classes after controlling for branch and firm-level characteristics.

Model (5) is a fixed-effects conditional logit model. Contrary to models (1)-(4) that estimate effects both within and between individuals, model (5) only focuses on the estimation of within-individual effects. In other words, it looks at the effects of intragenerational class mobility on informal employment and shows if the change of class is associated with the change of the probability of informal employment. If this is the case then time-constant unobserved preferences cannot by themselves explain class differences in employment contracts.[2] To estimate a fixed-effects model, the outcome variable needs to vary across time for the same individuals. This is the case for the 760 people in the sample who were employed formally and informally at different points in time.

As shown in Table 2, class effects in the fixed-effects model are consistent with the random-effects models. However, the differences in the coefficients between the routine and other classes are smaller in the fixed-effects model. Interestingly, lower technical workers in this model have a higher probability of informal employment compared to routine workers.

The logit coefficients presented in Table 2 do not give a direct indication of class-specific probabilities of informal employment. Predicted probabilities, computed for model 2, are presented in Figure 5.[3] The figure shows

[2]This also rules out the possibility that differences in employment contracts can be explained by education. While education is not a time-constant variable, people rarely get educational qualifications after age 25. When education is added as a control to model (5), it does not change the class effects and is not significant at the conventional level.

[3]To predict probabilities of the outcome reported in figures 5 and 12 I use population-averaged rather than random-effects logit models. The probabilities predicted from the population-averaged models more directly correspond to the proportions of the positive outcome in groups formed by the predictors. For details see Rabe-Hesketh and Skrondal

Table 2: Regression models for informal contracts[a]

	(1)		(2)		(3)		(4)		(5)	
variables	coef	se	coef	se	coef	se	coef	se	coef	se
ESeC class (ref. routine)										
1a/2a.Managers	-1.58***	(0.24)	-1.66***	(0.25)	-2.00***	(0.35)	-1.06***	(0.36)	-0.83*	(0.46)
1b.Higher professionals	-2.36***	(0.20)	-2.08***	(0.22)	-2.01***	(0.28)	-1.86***	(0.39)	-1.52**	(0.49)
2b.Lower professionals	-1.87***	(0.14)	-1.24***	(0.15)	-1.37***	(0.20)	-1.16***	(0.27)	-0.52**	(0.26)
3.Intermediate	-0.59***	(0.14)	-0.82***	(0.15)	-1.02***	(0.19)	-0.89***	(0.26)	-0.25	(0.27)
6.Lower supervisors	-0.42***	(0.14)	-0.49***	(0.14)	-0.46**	(0.18)	-0.64**	(0.27)	-0.40*	(0.23)
7.Lower sales and services	0.69***	(0.10)	0.22*	(0.11)	-0.25	(0.16)	0.08	(0.18)	0.28	(0.23)
8.Lower technical	0.19**	(0.10)	0.09	(0.10)	0.02	(0.13)	0.00	(0.17)	0.41**	(0.19)
Male			0.20**	(0.08)	0.22**	(0.11)	-0.14	(0.13)		
Age			-0.23***	(0.02)	-0.21***	(0.02)	-0.20***	(0.03)	-0.30***	(0.11)
Age squared/100			0.25***	(0.02)	0.23***	(0.03)	0.23***	(0.03)	0.51***	(0.10)
Sector (ref. private)										
State sector			-2.80***	(0.13)	-2.77***	(0.20)	-2.42***	(0.22)	-2.32***	(0.23)
Enterprise size (ref. small)										
Large(>49 workers)			-1.93***	(0.09)	-1.71***	(0.11)	-1.66***	(0.17)	-1.19***	(0.14)
No answer			-1.11***	(0.09)	-0.75***	(0.12)	-1.06***	(0.16)	-1.19***	(0.14)
Location (ref. city)										
Town			-0.59***	(0.09)	-0.51***	(0.12)	-0.53***	(0.15)		
Countryside			-0.75***	(0.10)	-0.52***	(0.13)	-0.93***	(0.16)		
Branch (ref. industry)										
Construction					1.60***	(0.16)				
Transport/communication					0.54***	(0.18)				
Agriculture					0.40	(0.25)				
Education, health, etc.					0.53**	(0.21)				
Trade/services					1.31***	(0.15)				
Others					0.29	(0.20)				
Firm founded in (ref. <1992)										
New (>1991)							1.51***	(0.22)		
No answer							1.27***	(0.21)		
Constant	-4.63***	(0.14)	2.16***	(0.34)	1.74***	(0.43)	1.12**	(0.54)		
Observations	33578		33578		15970		12656		2903	
Individuals	11318		11318		8197		6972		760	
Intraclass correlation ρ	0.48		0.39		0.38		0.14			

[a] The dependent variable is a dummy equal one if the contract is informal. (1)-(4) are logit models with random effects, (5) is a conditional logit model (equivalent to "fixed effects"). Dummy variables for years are included in all models, but not shown. The analytical sample includes years 1998, 2000, 2002-06. Branch of the economy is only available in years 2004-06, year of the foundation of the firm in years 1998, 2000, 2002. *** p<0.01, ** p<0.05, * p<0.1

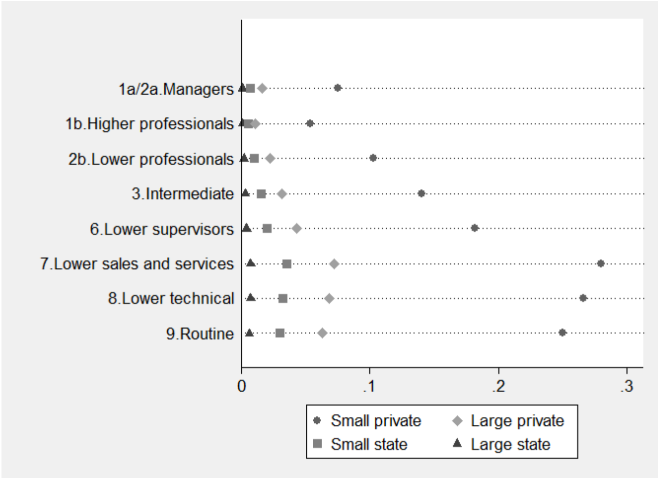

Figure 5: Probabilities of informal employment calculated from the population-averaged model with the same predictors as in model (2) in table 2. Other variables set at the following values: man, 40 years old, living in a city, year 2006.

class-specific probabilities of informal employment for large and small firms in private and state sectors, while setting other variables in the model at a fixed level (man, 40 years old, living in a city, in 2006).

As follows from the figure, the probabilities of informal employment in the state sector and in large firms in the private sector are close to zero for all classes. Class differences in informal employment are only important for people working in small private firms. If we added interaction effects between class and the sector of the economy and enterprise size, the contrasts between the sectors would likely be even sharper. However, as the predicted probabilities of informal employment are close to zero in all sectors, even in the model without interaction effects, except in small private firms (so that the coefficients for class are largely driven by the differences between employees in this sector), I omit interaction effects from the model to keep things simple (see sections 7 and 8 for the models with interaction effects).

For people working in small private firms, the pattern is consistent with Goldthorpe's class theory. Managers and professionals have the lowest probability of informal employment, and the working class have the highest probabilities. The classes with mixed employment contracts (intermediate workers and lower supervisors and technicians) are in the middle. It is interesting

(2008).

to note, though, that there is not much differentiation in the probabilities of informal employment within these groups. The probabilities for managers and higher professionals are similar. Both lower sales and services and skilled lower technical workers have higher chances of informal employment than routine workers, although the difference between these groups is small.

The RLMS also asks a question about the reasons for informal employment. Two possible answers offered to the respondents are that the employees themselves do not want a formal contract (35% of the sample) or that the employers do not want to sign a formal agreement (65% of the sample). Are there systematic class differences in these groups of people? To investigate this, I run regression models that are similar to models (1) and (2)[4], but with the outcome variable that identifies the voluntary or involuntary character of informal employment. The results are shown in Table 3.

The models show that for managers, manual supervisors, higher professionals and the intermediate class informal employment is more likely to be voluntary. On the other hand, for skilled and unskilled manual workers and lower professionals informal employment is more often involuntary (although, as shown above, for lower professionals it is quite rare). This is another piece of evidence in support of the argument about the consistency of class differences in employment contracts in Russia with Goldthorpe's class theory. Not only do non-manual classes have lower risks of informal employment, but they are also more likely to initiate verbal agreements themselves.

As can be seen from the descriptive statistics and predicted probabilities, informal employment only affects the minority of Russian workers. Now I proceed to another outcome variable, fringe benefits, that is relevant for all employees.

7 Class and fringe benefits

Are the differences in the number of fringe benefits among Russian employees class-related? Some labour economists considered fringe benefits to be an

[4]The sample includes only informally employed people and the average number of observations per person is less than two. This shows that informal employment usually does not have a long-term character. Technically, in the models presented in Table 3 I use logit models with clustered standard errors instead of random-effects logit models. Individuals are treated as clusters.

Table 3: Regression models for voluntary/involuntary informal employment[a]

	(1)		(2)	
variables	coef	se	coef	se
ESeC class (ref. routine)				
1a/2a.Managers	-1.16**	(0.47)	-1.17**	(0.46)
1b.Higher professionals	-0.33	(0.47)	-0.24	(0.47)
2b.Lower professionals	-0.01	(0.29)	-0.09	(0.29)
3.Intermediate	-0.40	(0.25)	-0.59**	(0.27)
6.Lower supervisors	-0.44*	(0.23)	-0.49**	(0.23)
7.Lower sales and services	0.23	(0.17)	-0.04	(0.20)
8.Lower technical	0.12	(0.16)	0.07	(0.16)
Male			-0.40***	(0.15)
Age			0.09***	(0.03)
Age squared/100			-0.13***	(0.03)
Sector (ref. private)				
State			-0.67**	(0.28)
Enterprise size (ref. small)				
Large(>49 workers)			0.07	(0.16)
No answer			0.05	(0.15)
Location (ref. city)				
Town			0.19	(0.16)
Countryside			0.35**	(0.17)
Constant	0.99***	(0.29)	-0.16	(0.56)
Observations	1521		1521	

[a] Dependent variable: a dummy for reasons for informal employment (1 if an employer does not want a formal contract, 0 if an employee does not want a formal contract). Logit regression with clustered standard errors where individuals are treated as clusters. Dummy variables for years are included in both models, but not shown. *** p<0.01, ** p<0.05, * p<0.1

impediment for labour mobility and effective labour allocation in Russia (see Clarke, 1999, for a discussion). In the Soviet period, some enterprises, especially large ones, often provided their workers not only with standard fringe benefits, such as paid holiday and sick leave, but also with free housing, sanitariums, children's and recreational facilities. It was suggested that in the post-Soviet period employees often stayed at inefficient Soviet enterprises, despite low pay, because of the fringe benefits provided.

According to this logic, fringe benefits are determined at the firm level and after controlling for firm characteristics we should not expect fringe benefits to vary by class. On the other hand, the theory of social class suggests that employers can provide more fringe benefits to employees in managerial and professional positions in order to secure more stable employment relationships.

To test this empirically, we need to construct a measure for fringe benefits. The binary variables for fringe benefits provided in the RLMS were listed in section 3. I excluded two of them, paid leave for pregnancy and child care (as this is relevant mainly for women), and subsidized rent for housing (this question was not asked in many rounds of the RLMS). With the remaining variables, I constructed a scale with the pooled RLMS sample using the summated rating model (i.e., simply summing up all the binary variables). Cronbach's alpha of the eight-item scale is 0.72, and no variable can be excluded to increase it.

The summated rating scale assumes that all variables have similar frequency distributions. This is clearly not the case in our data set. Some fringe benefits, such as paid vacations and sick leave, are more "popular", but others are less frequent. 88% of people in the pooled sample were provided with paid vacations, but only 9% reported full or partial payment for child care. Paid vacations and sick leave are the fringe benefits that are provided for the majority of workers, while free child care is much more rare. It is likely that those who have free child care tend to have paid vacations and sick leave as well. If this is the case, the summated rating model should be replaced by the Mokken scale (van Schuur, 2003).

Practically, the Mokken scale is constructed in the same way as the usual summated rating scale. However, it makes other distributional assumptions and its fit to the data should be tested with other statistical criteria. Instead of Cronbach's alpha, I use the Loevinger homogeneity coefficient H that is defined as the ratio of the total sum of errors observed to the sum of the errors expected in the model of stochastic independence. An error is a situation when a person gives a positive response to a more "difficult" item, but does not give a positive response to a more "simple" item (in our case, for example, has free child care, but not paid vacations). Stochastic independence implies that all systematic variation in responses is due to the latent trait that is measured by the scale (for details see van Schuur, 2003). Robert Mokken suggested that in order to satisfy the assumption about the cumulative character of the scale, the homogeneity coefficient of the scale H and all item coefficients H_i must be higher than 0.3. If we apply this criterion to our case, all the items in the scale satisfy it, except for "Free or discounted food or payment for food". This makes substantive sense, as provision with free food can depend on other factors than the latent dimension of fringe benefits. If we exclude this item, H for the seven-item scale is 0.49. Overall, the scales produced with the summated rating and Mokken models are similar and differ with only one item. In the subsequent analysis I use the seven-item Mokken scale.

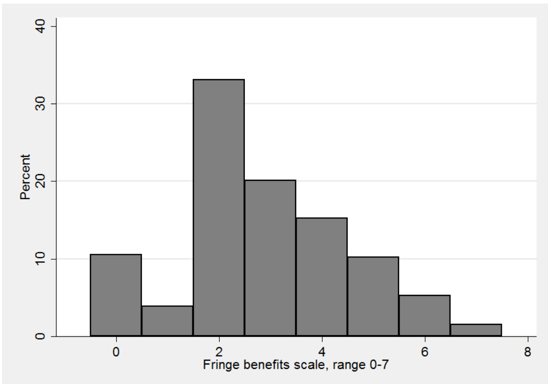

Figure 6: Distribution of the seven-item scale of fringe benefits

Figure 6 shows the distribution of the seven-item scale in the pooled sample. Note that the distribution has a positive skew, with the peak at two. This is an indication that many jobs provide two basic fringe benefits, paid vacations and sick leave. These two benefits are rarely separated, as indicated by the rare occurrence of one on the scale. About 10% of jobs have no fringe benefits at all.

Figure 7 is a time series plot of the mean of the fringe benefits scale

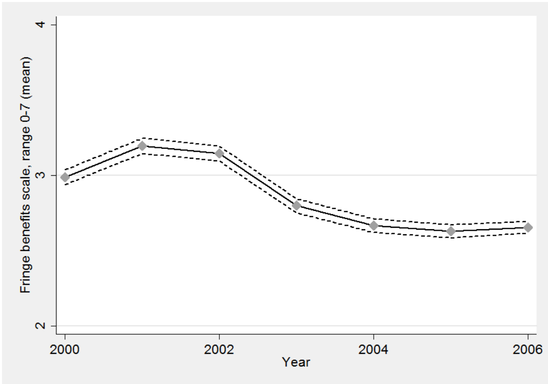

Figure 7: The mean of the seven-item fringe benefits scale, 2000-2006. Dashed lines show 95% confidence intervals around the mean.

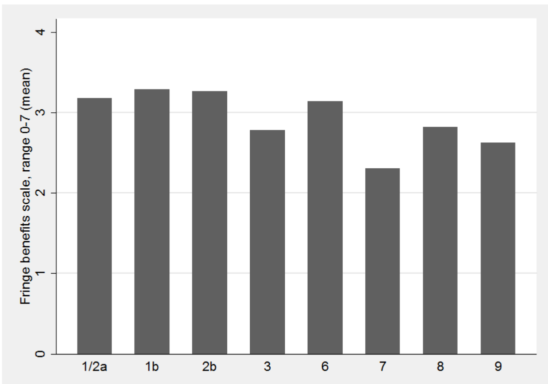

Figure 8: Mean of the seven-item fringe benefits scale across ESeC classes, 2000-2006. 1/2a - managers, 1b - higher professionals, 2b - lower professionals, 3 - intermediate, 6 - lower supervisors and technicians, 7 - lower sales and services, 8 - lower technical, 9 - routine.

in 2000-2006. It shows that the average number of fringe benefits provided decreased from 2002 to 2004, perhaps as a result of the introduction of a more liberal Labour Code in 2002.

Figure 8 demonstrates the difference in the mean score on the fringe benefits scale across the ESeC classes. The differences between classes are not very large, but the service relationship classes on average do have more fringe benefits than the labour contract classes. The regression analysis tests if the differences are statistically significant and if they remain after controlling for other variables.

Table 4 shows the coefficients from the regression models that are similar to those presented in the previous section on informal contracts. In the first model I regress the fringe benefits scale on class and dummy variables for years. The differences in fringe benefits between classes are significant and in the theoretically expected direction. Higher professionals are the class with the most fringe benefits, and lower sales and service workers have the fewest fringe benefits. The difference between these two groups in the mean value of the seven-item scale of fringe benefits is 0.91. However, the R^2 of the model is low. Class and year jointly explain only 6% of the variance of the scale of fringe benefits.

Model 2 adds control variables: sex, age, economic sector, enterprise size and location. The average number of fringe benefits for men and women does not differ. Age has a concave association with fringe benefits. People working in the state sector and in large enterprises on average have more fringe benefits compared to the private sector and small enterprises.

Models 3 and 4 control for the branch of the economy and the year of the foundation of the enterprise, the variables that are available only for some years of the survey. Heavy and light industry is the branch with the most fringe benefits, while construction and trade and services have the smallest number of benefits. New firms created in the post-Soviet period provide fewer fringe benefits.

All the models presented so far assumed that the association of class with the number of fringe benefits is constant across the different sectors of the economy. The coefficients presented for class were averaged across private and state and large and small firms. As this is not necessarily the case, I fit another model that is based on model 2 from table 4, but also includes

Table 4: Regression models for the scale of fringe benefits[a]

	(1)		(2)		(3)		(4)		(5)	
variables	coef	se	coef	se	coef	se	coef	se	coef	se
ESeC class (ref. routine)										
1a/2a.Managers	0.48***	(0.05)	0.43***	(0.05)	0.54***	(0.06)	0.41***	(0.07)	0.14**	(0.06)
1b.Higher professionals	0.65***	(0.04)	0.52***	(0.04)	0.50***	(0.05)	0.40***	(0.05)	0.28***	(0.06)
2b.Lower professionals	0.55***	(0.03)	0.40***	(0.03)	0.49***	(0.04)	0.31***	(0.05)	0.13***	(0.05)
3.Intermediate	0.21***	(0.04)	0.20***	(0.04)	0.28***	(0.05)	0.31***	(0.06)	0.05	(0.05)
6.Lower supervisors	0.37***	(0.04)	0.34***	(0.04)	0.36***	(0.05)	0.35***	(0.06)	0.19***	(0.04)
7.Lower sales and services	-0.26***	(0.04)	-0.15***	(0.04)	0.13***	(0.05)	-0.12**	(0.06)	-0.19***	(0.05)
8.Lower technical	0.13***	(0.03)	0.11***	(0.03)	0.12***	(0.04)	0.05	(0.05)	0.03	(0.04)
Male			0.03	(0.03)	0.03	(0.03)	0.08**	(0.04)		
Age			0.05***	(0.01)	0.04***	(0.01)	0.05***	(0.01)	0.08**	(0.03)
Age squared/100			-0.05***	(0.01)	-0.04***	(0.01)	-0.05***	(0.01)	-0.10***	(0.02)
Sector (ref. private)										
State sector			0.56***	(0.02)	0.51***	(0.03)	0.47***	(0.03)	0.37***	(0.02)
Enterprise size (ref. small)										
Large(>49 workers)			0.70***	(0.02)	0.57***	(0.03)	0.70***	(0.03)	0.41***	(0.02)
No answer			0.36***	(0.02)	0.31***	(0.03)	0.40***	(0.04)	0.16***	(0.03)
Location (ref. city)										
Town			0.27***	(0.03)	0.26***	(0.04)	0.25***	(0.04)		
Countryside			-0.02	(0.03)	0.01	(0.04)	-0.11***	(0.04)		
Branch (ref. industry)										
Construction					-0.74***	(0.05)				
Transport/communication					-0.29***	(0.05)				
Agriculture					-0.43***	(0.06)				
Education, health, etc.					-0.29***	(0.04)				
Trade/services					-0.98***	(0.04)				
Others					-0.44***	(0.04)				
Firm founded in (ref. <1992)										
New (>1991)							-0.74***	(0.04)		
No answer							-0.49***	(0.03)		
Constant	2.59***	(0.03)	0.84***	(0.11)	0.57***	(0.13)	1.30***	(0.16)	2.38***	(0.04)
Observations	34811		34811		16095		13679		34811	
Individuals	10962		10962		8231		6696		10962	
R^2	0.06		0.17		0.21		0.18		0.15	
Intraclass correlation ρ	0.51		0.44		0.50		0.46		0.60	

[a] The dependent variable is a 7-item scale for fringe benefits. (1)-(4) are linear regression models with random effects, (5) is a fixed-effects model. Dummy variables for years are included in all models, but not shown. The analytical sample includes years 2000-06. The branch of the economy is only available in years 2004-06, the year of the foundation of the firm in years 2000-02. The data on informal contracts are unavailable for year 2001. *** p<0.01, ** p<0.05, * p<0.1

Figure 9: Predicted mean values on the seven-item fringe benefits scale, by class and sector. Calculated from model (2) + interaction effects between class and firm size and class and sector. Other variables set at the following values: man, 40 years old, living in a city, year 2006.

the interaction effects between class and the size of the enterprise[5] and class and the sector of the economy (state vs. private). As this model contains a large number of terms that result from the interactions of categorical variables, I do not present the coefficients in the table. Instead I calculate the predicted mean number of fringe benefits (on the seven-point scale) for all the combinations of class, the enterprise size and sector, and present the results in Figure 9. The other variables in the model were held at the following values: man, aged 40, living in a city, in 2006.

The class differences in fringe benefits are in general consistent with Goldthorpe's class theory. In all economic sectors, the salariat on average have more fringe benefits than the working classes. However, the size of the effect of class is quite small. For example, the difference in the average number of fringe benefits measured on the seven-item scale between managers and routine workers is only from 0.4 to 0.6 points, depending on the sector. The effect of the type of enterprise is much stronger. Lower sales and service workers employed in large state enterprises have on average 3.5 fringe benefits (other variables held at the values specified above), while in small private firms they only have on average 1.6 fringe benefits.

[5]To reduce the number of interaction terms, I combine small enterprises and enterprises with an unknown size and after that compare large and small enterprises.

Workers employed in large state enterprises have the most benefits, followed by workers in small state and large private firms (who are approximately equal in terms of fringe benefits). Workers in small private firms have the fewest non-monetary rewards.

There is not much difference in fringe benefits between managers and professionals. Higher professionals tend to have more fringe benefits than lower professionals, but the difference between them is minuscule. There is virtually no difference in fringe benefits between managers and lower supervisors and technicians. This result contradicts Goldthorpe's theory.

Lower sales and service workers have the lowest number of fringe benefits if they are employed in the private sector. However, in the state sector they are at about the same level as intermediate workers.

Lower technical and routine workers have the fewest fringe benefits (apart from the private sector where lower sales and service workers are the least disadvantaged). There is little difference between lower technical and routine workers.

Finally, model 5 in table 4 is the model with fixed effects that estimates the effects of class on fringe benefits within individuals. The results are generally consistent with the random-effects models. However, note that in the fixed-effects model the effect for higher professionals is twice as large as that for managers or lower professionals. Being a lower supervisor has about the same effect on fringe benefits as for managers and lower professionals. Being in the lower sales and service class has the worst effect on fringe benefits.

8 Class and unemployment risks

The last outcome variable I consider in this paper is unemployment. This is one of the variables that Goldthorpe and McKnight (2006) used in the validation of the NS-SeC schema for Britain. The service classes in Britain had lower unemployment risks than the manual classes.

Figure 10 compares the dynamics of the official unemployment rate calculated by the Russian Statistical Office (Rosstat, 1999-2009), with the unemployment rate in the RLMS. Unemployment peaked in 1998, the year of a major economic crisis in Russia, and declined after that. For the 1990s the RLMS gives somewhat lower estimates for unemployment, compared

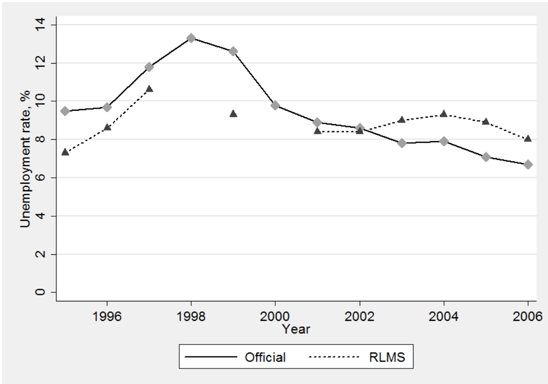

Figure 10: Unemployment rates in Russia, people aged 15-72. The solid line represents the official estimates of the Russian Statistical Office. The dashed line represents the estimates based on the RLMS.

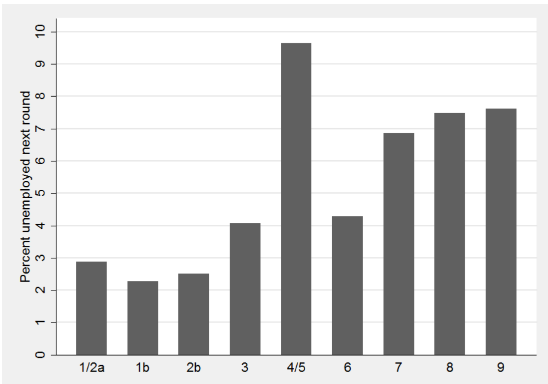

Figure 11: Percent of unemployed in the next RLMS round across the ESeC classes, 1994-2005. 1/2a - managers, 1b - higher professionals, 2b - lower professionals, 3 - intermediate, 4/5 - self-employed, 6 - lower supervisors and technicians, 7 - lower sales and services, 8 - lower technical, 9 - routine.

Table 5: Regression models for unemployment risks[a]

	(1)		(2)		(3)		(4)	
variables	coef	se	coef	se	coef	se	coef	se
ESeC class (ref. routine)								
1a/2a.Managers	-1.08***	(0.17)	-0.79***	(0.17)	-0.90**	(0.40)	-0.62***	(0.19)
1b.Higher professionals	-1.39***	(0.12)	-0.94***	(0.12)	-1.08***	(0.30)	-0.84***	(0.15)
2b.Lower professionals	-1.25***	(0.09)	-0.93***	(0.10)	-0.95***	(0.23)	-0.84***	(0.12)
3.Intermediate	-0.74***	(0.12)	-0.54***	(0.12)	-0.40*	(0.23)	-0.71***	(0.16)
4/5.Self-employed	0.26**	(0.10)	0.03	(0.11)	-0.50	(0.45)	-0.10	(0.15)
6.Lower supervisors	-0.65***	(0.11)	-0.50***	(0.11)	-0.62**	(0.26)	-0.45***	(0.14)
7.Lower sales and services	-0.11	(0.08)	-0.04	(0.09)	-0.45**	(0.21)	-0.04	(0.11)
8.Lower technical	0.00	(0.07)	0.02	(0.07)	-0.22	(0.17)	0.06	(0.09)
Male			0.38***	(0.06)	0.35**	(0.13)	0.32***	(0.07)
Age			0.02	(0.01)	0.02	(0.03)	0.02	(0.02)
Age squared/100			-0.08***	(0.02)	-0.06*	(0.04)	-0.08***	(0.02)
Sector (ref. private)								
State sector			-0.33***	(0.05)	-0.10	(0.14)	-0.26***	(0.07)
Enterprise size (ref. small)								
Large(>49 workers)			-0.28***	(0.06)	-0.22*	(0.13)	-0.20**	(0.08)
No answer			0.05	(0.06)	0.03	(0.17)	-0.02	(0.09)
Location (ref. city)								
Town			0.05	(0.07)	0.08	(0.15)	-0.03	(0.08)
Countryside			0.63***	(0.06)	0.59***	(0.14)	0.54***	(0.08)
Branch (ref. industry)								
Construction					0.35	(0.24)		
Transport/communication					0.29	(0.23)		
Agriculture					0.85**	(0.22)		
Education, health, etc.					0.30	(0.23)		
Trade/services					0.68**	(0.20)		
Others					0.64**	(0.23)		
Firm founded in (ref. <1992)								
New (>1991)							0.31***	(0.10)
No answer							0.16**	(0.08)
Missing (informal sector)							0.49***	(0.14)
Constant	-3.11***	(0.09)	-2.89***	(0.28)	-3.18**	(0.63)	-2.70***	(0.35)
Observations	43887		43887		8755		25233	
Individuals	10630		10630		5378		8293	
Intraclass correlation ρ	0.31		0.29				0.24	

[a] Logit regression models with random effects (1, 2, 4) or clustered standard errors (3). The dependent variable is a dummy for being unemployed in the next round. The full sample includes years 1994-2005. Dummy variables for years are included in all models, but not shown. The branch of the economy is only available in years 2004-06, the year of the foundation of the firm in years 1995-2002. ***p<0.01, ** p<0.05, * p<0.1

to official data. For the 2000s, the RLMS estimates are somewhat higher. However, the time trends are the same and the discrepancy between the two data sources is not large.

Figure 11 shows unemployment rates across the ESeC classes in the pooled RLMS sample. Unemployment rates were calculated as the percent of people in respective occupational classes who were observed to be unemployed in the next RLMS round. We find the same pattern as with the two previous outcome variables. Managers and professionals have the lowest unemployment rates, followed by the intermediate class and lower supervisors and technicians. The lower sales and services, lower technical and routine classes have higher unemployment risks. For this variable, I did not exclude the self-employed from the analysis; they showed the highest level of unemployment. This demonstrates a high level of economic insecurity among the self-employed, although in other respects they were among the most economically successful groups in post-Soviet Russia (Gerber, 2001).

Table 5 presents the regressions models with the same variables as in two previous sections.[6] Men have higher unemployment risks than women (this is consistent with Gerber and Mayorova (2006)). The youngest and the oldest workers are most vulnerable to unemployment. Employees in the state sector and in large enterprises experience unemployment less often. The branches with the highest unemployment risks are agriculture and trade and services; the lowest risks are in industry. Workers employed in new firms lose their jobs more often.

Figure 12 shows the predicted probabilities of losing a job for classes in the firms of different type. As in the previous sections, the probabilities are based on model 2 with added interaction effects between class and firm size, and class and the economic sector (the regression coefficients for this model are not shown). Other variables in the model were set at the following values: man, aged 40, living in the city, in 2000. Low predicted probabilities should not be misleading, as they are the consequence of our operationalization of unemployment. These are probabilities of losing a job in the next RLMS round rather than experiencing unemployment in the whole period of the market transition. In the latter case, the probabilities would have been

[6] As in model 3 the maximum number of cases per individual is only two, I use logit regression with clustered standard errors instead of the random-effects model. The fixed-effects model includes only a very small number of cases (as it requires the same people to be employed and unemployed at various points of time) and is not presented.

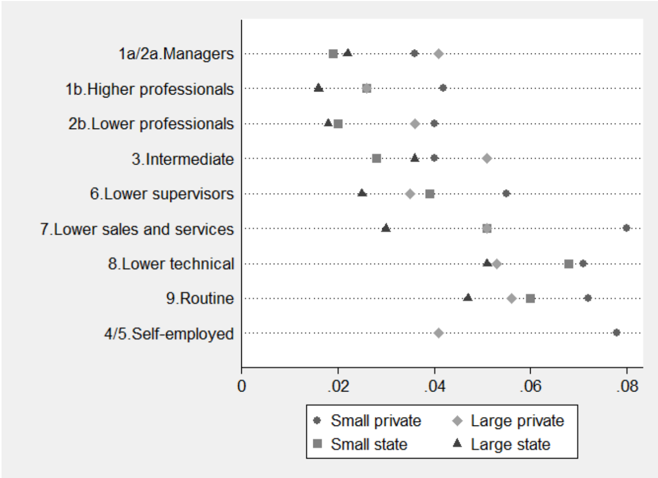

Figure 12: Probabilities of becoming unemployed in the next RLMS round, calculated from the population-averaged model with the same predictors as in model (2) in table 5 + interactions between class and firm size and class and the sector of the economy. Other variables set at the following values: man, 40 years old, living in a city, year 2000.

higher, but the pattern of class inequality would have been the same.

The figure shows that in general Goldthorpe's theory holds. As with the previous outcome variables, managers and professionals have the most advantaged position in the labour market. They have the lowest unemployment risks. Lower technical, routine and lower sales and services classes, on the contrary, have the highest unemployment risks. The intermediate class and lower supervisors are in the middle. This is consistent with the predictions of the theory.

It is interesting to compare class differences in unemployment risks with the differences across the types of the enterprises where workers are employed. Employees in small private firms are the most vulnerable, while in large state enterprises employees are the most protected. The difference in the probabilities of losing a job between employees in these two types of firms, controlling for class, is on average as large as the average difference between managers and routine workers.

Moreover, the strength of the association between class and the probability of unemployment depends on the type of enterprise. Lower sales and service workers in small private firms have unemployment risks that are about 2.5 times higher than the risks of lower sales and service workers employed in large state enterprises. On the other hand, for lower technical workers, this probability ratio is only 1.5.

There is not much difference in the probabilities of losing a job for managers, higher and lower professionals (except of the large private enterprises where higher professionals have lower unemployment risks). It is also hard to distinguish between lower technical and routine workers, at least in the private sector. In the state sector, the unemployment risks of lower technical workers are somewhat higher than for routine workers. In Britain, routine workers have a lower probability of unemployment compared to lower technical workers, although the difference is small (Goldthorpe and McKnight, 2006).

It should be noted that our estimation sample includes only workers who were present in the RLMS in two consecutive rounds. Therefore, it does not include people who dropped out from the study. As the attrition rate among manual workers is likely to be higher, this may bias the estimated size of the class difference in unemployment risks. However, this bias is unlikely to be large.

9 Summary of results

In this paper I have analyzed the associations of class with three variables: informal employment contracts, fringe benefits and unemployment risks. These variables that mainly measure job security were chosen in order to test the validity of the ESeC in Russia. To check if this class schema is valid, I tested whether ESeC classes are associated with job security in the way Goldthorpe's class theory predicts.

In general, the results confirm the validity of the application of the ESeC in Russia. The service class (managers and professionals) is the most privileged in terms of economic security. Managers and professionals have the lowest probability of informal employment, the lowest unemployment risks and the highest average number of fringe benefits. The labour contract classes (skilled and unskilled manual workers or, in the ESeC terminology, lower technical and routine workers and lower sales and services workers) are the least privileged. The mixed contract classes (intermediate workers and lower supervisors and technicians) occupy an intermediate position. These results are in agreement with previous findings by Evans and Whitefield

(2003) and indicate that the ESeC can be meaningfully applied in empirical research on the Russian economy and society.

However, the size of the effects of class varies in the enterprises of different types. Informal employment contracts are employed only in small private enterprises, and class differences are relevant just for this sector. The type of the firm is just as important a predictor of unemployment risks as class. Class patterns of unemployment risks differ depending on the economic sector, and the class gap in the probability of losing a job in small private and large state firms is somewhat larger than in large private enterprises.

The class effect on the number of fringe benefits is in the theoretically predicted direction, but it is quite small, especially compared with the effect of the firm type. Perhaps it is not surprising as the number of fringe benefits is arguably our weakest measure of economic security. The large number of fringe benefits can be only indirectly interpreted as a sign of the intention of an employer to establish long-term relationships with employees.

In the analysis I separated managers and professionals (this is a deviation from the ESeC) in order to test if there are differences in economic security between these two groups of workers. The results do not identify the differences, despite the fact that the incomes and social mobility patterns of these two groups in Russia are clearly different (Gerber and Hout, 1998, 2004; Bian and Gerber, 2008). This is consistent with the theoretical justification of the EGP and ESeC class schemes and the results for Britain reported by Mills in McGovern et al. (2007). Both Goldthorpe and Mills argue that managers and professionals should not be treated as two separate classes if the classification is based on the type of employment contract.

The ESeC does not perform well in the differentiation of classes within the service class and the working class in Russia. Higher and lower professionals, as well as skilled and unskilled manual workers, are very similar in respect to the outcome variables analyzed in this paper. This is hardly a specifically Russian problem. In the latent class analysis of class-relevant job characteristics, Evans and Mills (1998, 1999, 2000) failed to find separate latent classes for the higher and lower salariat, and for skilled and unskilled manual workers (as defined by the EGP class schema). Further research is required to identify the theoretical reasons for the separation among these classes within the salariat and the working class.

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