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Leaving State Jobs in Russia

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Abstract

I analyze the reallocation of labor and human capital from the state sector to the nonstate sector and nonemployment in Russia. I use a nationally representative household data set, the Russian Longitudinal Monitoring Survey, to study sectoral mobility in two periods of transition using multivariate discrete choice models. The results show that sectoral mobility of different skill groups varies. Those with university education, with supervisory responsibility and in white-collar occupations are less likely to leave state jobs to both nonstate employment and nonemployment. The results suggest that there may be mismatch of skills across state/nonstate employment and that nonstate employment consists mostly of low skill, bad jobs.

Keywords: labor mobility, human capital, privatization.
JEL classification: J4, J6, P2.

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1 Introduction

One of the decisive factors of success in transition from plan to market is the reallocation of labor and human capital from the state to the private sector. The reallocation of labor determines growth of the new private sector. The private sector requires workers and their skills – educated professionals, skilled machine-operators, as well as those with a knack for adapting to the new environment – in order to grow and be productive. The reallocation of labor also determines economic performance both during and after transition. During transition, the extent of unemployment and economic costs associated with it, such as lost income, deteriorating skills and underuse of human resources, depend on the nature of the reallocation process. In the long run, assuming that the private sector is more efficient in its use of resources, the growth potential of the economy is decided by the reallocation of human capital to the private sector. Further, any human capital inherited from the plan economy that is not useful in the new economic environment constitutes lost investment.

The Russian experience in reallocation of labor and human capital is mixed. The apparently positive features include fast privatization, high job turnover and low unemployment. First, as a result of the mass privatization program, the share of private employment and production increased rapidly. After only three years of transition in 1994, 50 per cent of Russian GDP was produced by private firms. Second, job mobility as measured by job turnover has been relatively high in Russia during transition. Remarkably, up until 1996 nearly half of all jobs involved a hire or a separation within a year (Gimpelson and Lippoldt, 1997). Third, in contrast to other transition economies, the Russian unemployment rate remained below 10 per cent during the early part of the transition. These features together with a downward adjustment of real wages, encouraged the OECD to conclude that the flexible Russian labor market was "one of the most encouraging aspects of economic performance" in Russia (p.143, OECD, 1995). The negative features of labor reallocation in Russia include labor hoarding and poor output performance. Russian firms hoarded labor in masses. The extent of labor hoarding is evident from comparing output and employment growth figures between 1992 and 1995: while output fell by a total of 35.5 percent, employment declined by 10.5 per cent only. The fall in output itself has been the largest among the transition economies. Finally, a closer look at some of the apparently positive features suggests that labor market performance may have not been so encouraging after all. In particular, studies of labor mobility have found that job mobility is lower for those with more education and higher skills, suggesting that the reallocation of some types of human capital may have been slow (Gimpelson and Lippoldt, 1997, Grosfeldt *et al.*, 1999 and Turunen, 2000).

In this study I evaluate a particular aspect of reallocation of labor and human capital in Russia: the role of skills and human capital in the decision to leave state jobs. The study contributes to existing knowledge of worker mobility in Russia in three directions. First, I evaluate labor mobility over employment states *by ownership* versus moves between employment and nonemployment *per se*. In particular I study the determinants of leaving state jobs to other employment states, i.e. nonstate employment and nonemployment. The focus on employment states by ownership underlines the importance of reallocation from the state to the private sector. Second, the emphasis on employment by ownership allows me to indirectly evaluate the nature of the private sector. In a recent study, Gimpelson and Lippoldt (1999), evaluate private sector employment directly using various data sources. As all studies of the private sector in Russia, their study suffers from the difficulty of consistently measuring private employment. Third, I compare the determinants of leaving state jobs in two different time periods of Russian transition.

I use a household data set, the Russian Longitudinal Monitoring Survey (RLMS) to study mobility between employment states by ownership. Three features of the RLMS data are particularly valuable for the study: first, the data is nationally representative of the Russian population; second, the panel structure of the data enables me to compare labor mobility over time; and third, the data allows for a consistent definition of firm ownership to state and nonstate. I estimate discrete choice models to evaluate the characteristics of those that leave state jobs within a year. The results show those with higher education, supervisory responsibility or in white-collar occupations are less likely to leave state jobs. The negative education effect is strongest for those with university education. The determinants of mobility change over time. In addition, a large part of the negative effect is driven by the structure of privatization that is biased towards blue-collar employment.

The rest of the paper is organized as follows. In section 2, I review existing literature on labor mobility and skills, and composition of the private sector in Russia. In section 3, I present the RLMS data and the samples used in the analysis, as well as definitions of employment states and skill proxies (a detailed discussion of methodology is included in an Appendix). In section 4, I present the results of the study in three subsections: sample characteristics, leaving state jobs using a logit model, and leaving state jobs to nonstate employment or nonemployment using a multinomial logit model. In section 5, I discuss alternative interpretations of the results. Finally, I summarize the study in section 6.

2 Literature

The studies of job mobility in Russia are limited by available data sources. As a result, most early studies adopted a case study approach or use fragmented sources of aggregate and cross-sectional data to evaluate mobility. These early studies point to a puzzling coexistence of relatively high labor turnover and continued labor hoarding in Russia. Several studies have confirmed that high turnover is an important feature of the Russian labor market. Using official aggregate statistics, Gimpelson and Lippoldt report that labor turnover was between 46 to 50 per cent before 1996, slowing down to approximately 42 thereafter. Comparable figures from other transition economies point to much smaller turnover, between 32 to 42 per cent (Gimpelson and Lippoldt, 1997).[1] However, based on aggregate data, labor hoarding was also common. Between 1992 and 1995,

[1] Gimpelson and Lippoldt stress that the o± cial statistics are likely to understate the extent of labor turnover in Russia, mainly because of the exclusion of small en-

the time period of this study, output fell by a total of 35.5 percent while employment declined by 10.5 per cent. The difference between declines in output and employment suggests that a large employment overhang persisted during the transition. Various explanations for this extensive labor hoarding have been suggested in the literature. These explanations include the structure of decision making within firms, technological constraints, various institutional factors of the labor market and sociocultural factors (for a discussion, see Commander *et al.* articles in World Bank, 1995, Metalina, 1996 and Standing, 1996).

The coexistence of high labor turnover and labor hoarding suggests that labor turnover varies for groups of workers with different characteristics. Two studies have explicitly looked at the extent of differentiation. Gimpelson and Lippoldt were the first to point out the segmentation of the Russian labor market by turnover (Gimpelson and Lippoldt, 1997). First, they cite case study evidence that in the Russian industry most hires are either workers with specific high skills or those with poor skills, and particularly young workers. The case studies also suggest that low skill workers are more likely to separate than high skill workers. This evidence is supported by official aggregate data that confirms that those in blue-collar occupations and the young are more likely to be hired and to separate. Gimpelson and Lippoldt also look at the covariates of job tenure in the 1995 round of the RLMS. They find that those with short tenure are more likely to be young, less educated and to work in small, private firms. In total, the evidence provided by Gimpelson and Lippoldt points towards a large degree of segmentation in terms of skills and labor mobility (Gimpelson and Lippoldt, 1997). In a recent study Grosfeldt *et al.* (1999) look for evidence of segmentation using a panel of enterprise data. Their results confirm segmentation by skill. They find out that employment of blue-collar workers, as opposed to white-collar workers, is more responsive to idiosyncratic shocks to firm output. In their analysis, they are able to control for various firm characteristics and for unobserved heterogeneity across firms (Grosfeldt *et al.*, 1999).

Additional evidence of the labor reallocation process is provided by

terprises (Gimpelson and Lippoldt, 1997).

studies that use the RLMS to describe worker mobility. Foley (1997) examines transitions of workers between employment states. His results confirm high labor mobility in Russia and point to various individual characteristics as determinants of transitions between employment states. He estimates multinomial logit models to study the determinants of transitions between old employment, new employment, unemployment and out of the labor force.[2] The main characteristics that determine transitions from employment to nonemployment are sex, age, education and sectors by ownership. In particular, he finds that university education reduces the probability of moving to unemployment or out of the labor force. However, he does not find any effect of education in moving to new jobs. Also, working in a state firm reduces the probability of moving to unemployment or out of the labor force, and to new jobs. In contrast, working in a private firm increases the probability of moving to both states. In summary, the results point to the importance of both sectors by ownership and skills as determinants of employment transitions (Foley, 1997). In a closely related study Lehmann and Wadsworth (1998) repeat Foley's multinomial logit analysis using data from 1994 onwards. The results related to education and sectors by ownership are identical. In particular, both studies find no evidence that education is a significant determinant of moves to new jobs. Looking at separations from the state sector, Lehmann and Wadsworth find only a weak negative effect of education on moves to nonemployment. In addition, they study determinants of turnover and new jobs. They find that turnover is higher in the private sector and lower for those that are older and those with high tenure. These results seem to confirm that ownership does have a strong impact on job mobility. To study new jobs, Lehmann and Wadsworth use a regional supplement of the Russian Labor Force Survey (LFS) from 1996. They find that workers in new jobs are less likely to be in managerial/professional occupations or female (Lehmann and Wadsworth, 1998). This seems to provide evidence that a majority of new jobs are for low skill workers. In Turunen (2000), I use the RLMS

[2] Foley (1997) uses data from both the first and the second phase of the RLMS. Unfortunately the data in the first phase does not allow for a correct classification of moves to new employment.

data to evaluate mobility across employment states by ownership. The results confirm that those with lower education are more mobile across employment states by ownership. This is particularly true if mobility is restricted to between state and nonstate employment only (Turunen, 2000).

Finally, a recent study by Gimpelson and Lippoldt provides evidence about the composition of the private sector (Gimpelson and Lippoldt, 1999). They use official aggregate statistics, as well as microdata, to evaluate the size and composition of private employment. They find conflicting results on the composition of private employment depending on the data source. The robust results include the observations that those in private sector employment are younger and relatively more likely to be in blue-collar occupations. In addition, the data suggests a differentiation within the private sector across education: the private sector includes both those with high education and those with low education, while those with intermediate degrees are more likely to be in the state sector. In general the results point to large variation across regions, firm size and sectors. Gimpelson and Lippoldt conclude that the private sector is characterized by greater labor turnover, younger and probably more adaptable workers.

3 Data and definitions

I use the RLMS to evaluate the determinants of transitions between employment states by ownership. For the analysis I combine rounds 1 and 3, and rounds 5 and 6 of the RLMS to build two short panels that cover 1992-1993 and 1994-1995, respectively.[3] This strategy allows me to have two comparable samples of the Russian population at two different periods of transition. During the first period, the Russian economy was characterized by a large fall in output, macroeconomic instability and

[3] The RLMS consists of eight rounds of surveys between 1992 and 1998. As a result of changes in the sampling procedure in 1994 the data constitutes two separate longitudinal panels.

emerging unemployment. Privatization was at an early stage. During the second period the fall in output slowed down, the macroeconomy stabilized, while unemployment continued to rise. The mass privatization program, started in October 1992, was in full swing.

In order to construct the samples used in the study, I merge data on individuals from consecutive rounds and restrict the data to those between 16-72 years old. The results are comparison samples that are used to verify representativeness of the constructed variables. In the process of building the comparison sample I lose a number of observations due to attrition, missing/conflicting data and the age restriction.[4] Survey timing, number of observations in the original data and in the samples used is documented in Table 1. The smaller number of observations in the second period reflects a change in the sampling procedure of the original data. Comparing the sample characteristics before and after eliminating data confirms that the selection to the comparison sample is approximately random.

In the analysis below I am interested in the role of skill in worker mobility across employment states by ownership. Three measures of skills are available: education, supervisory responsibility and occupation. Unfortunately, only education and supervisory responsibility are available in both periods. Education is assumed to mainly measure general human capital. Some education categories, special secondary education in particular, also reflect more specific training that may be firm or sector specific. The constructed education categories roughly coincide with national categories. However, because of reclassficiation of all those with secondary vocational education in the special secondary education category, this category is overrepresented. The reclassification is necessary to keep the comparability of the two periods (for detail, see Turunen, 2000).[5] Contrary to education categories, supervisory responsibility is as-

[4] The RLMS is a survey of addresses and thus does not follow the original household when they move. This feature increases the number of individuals lost due to attrition.

[5] The original education categories in the two panels are slightly different. The education categories were recoded as follows. University education includes those who completed university or graduate school; Special secondary education includes those who completed special secondary education, technical school or secondary vocational

sumed to proxy higher job-specific skills and attachment to the job. The third skill proxy, white-collar occupation is a more standard measure of skills. White-collar occupation includes those in the first four ISCO categories: managers, professionals, technicians and associate professionals, and clerks. The rest are coded as blue-collar workers (i.e. service workers, skilled agricultural workers, craft and related trades workers, plant and machine operators and elementary occupations). An additional measure of skill is the hourly wage. Typically, the hourly wage measures both productivity and the quality of the job match. The hourly wage is constructed by dividing the after tax nominal wage of the previous month by hours worked in that month. The hourly wage constructed in this fashion is potentially measured with error. In addition, since both wage and hours worked information refer only to the previous month, hourly wage may not correctly measure longer term returns to the job. This is particularly true in the presence of wage arrears, common in the second period. In order to evaluate the robustness of the results I estimated all models in the study with and without hourly wage, and with monthly wage instead of the hourly wage. The results for the skill proxies remain the same.

The employment state by ownership is constructed using information on the main occupation of the respondent and ownership status of the enterprise. In both periods, the employment state is classified in three categories: state employed, nonstate employed and nonemployed. The employed include those employed in an enterprise, entrepreneurs and those involved in individual economic activity as main occupation. I use information on ownership to reclassify the employed to employed in either state or nonstate enterprise.[6] Finally, the nonemployed include

school and no university education; General secondary education includes those with 10 years or more at school and no university or special secondary education; and Primary includes those with less than 10 years of school and no other education.

[6] In detail the classification of ownership is as follows. Those in state employment include those who report working in state owned enterprise and/or a public association in the first period and those working in a government owned enterprise in the second period. Those in nonstate employment include those working in a privately owned, collectively owned (considered as privatized firms) and other type of firms, including

the unemployed as well as those normally classified as out-of-the labor force. The representativeness of the definition of the dependent variable is evaluated using information in Table 2. It seems that the state sector is overrepresented in the RLMS sample. There are two potential explanations. First, it could be that individuals simply do not have good information on the ownership of the enterprise. However, it is not obvious why this measurement error would be towards state firms. Second, the comparison data is from a survey of enterprises and may thus not be directly comparable. In general, it has turned out to be very difficult to evaluate the exact size of the state and nonstate sectors.

There are difficulties in using the employment state by ownership that go beyond measuring ownership correctly. First, it is possible that firms in the two sectors, state and nonstate, do not behave differently. Most theoretical models of transition assume that the two sectors are fundamentally different (for example, Aghion and Blanchard, 1994) . However, it is well understood in the transition literature that privatization does not necessarily lead to changes in the core strategies of the firm (see Blanchard, 1997). Unfortunately it is not possible to identify restructuring using household data. Thus the distinction used here is then taken as a proxy for potential restructuring and whether the two sectors are distinctly different remains an empirical question. Second, and related point is that precisely some of the changes from state to nonstate employment are name-plate changes that have no real effect on the strategy of the firm or the position of the employees. Various studies have suggested that privatized and new private firms behave very differently when it comes to employment decisions. For example, Gimpelson and Lippoldt (1999) point out that in many cases the mixed ownership firms (a common result of partial privatization) have turned out to have poorer economic performance as well as a less dynamic employment policy than fully private firms. Clearly, the extent to which the classification matters for the results depends on the period. The proportion of privatized jobs

firms that have mixed-ownership in the first period and those who report foreign or Russian individuals as the owner of the enterprise and any mixed-owned enterprises in the second period. In both periods the nonstate employed include also entrepreneurs and those engaged in individual economic activity as main occupation.

is low at the early part of transition, whereas it increases in the second period. I evaluate the importance of privatized jobs in the second period by separating those individuals who made a real job move to the nonstate sector from those whose firm was simply privatized. Unfortunately no information on the latest job move is available in the first period.

In the analysis I consider only those in working age, i.e. I exclude those younger than 18 and older than 54 for women and 59 for men. The full samples are used to evaluate selection into state employment. Finally, I construct the samples used in the multivariate analysis by excluding those not employed in a state owned enterprise in the first round of each panel. In the process, I also exclude those with missing information on the control variables. However, because of the growing importance of wage arrears and unpaid leave those whose main occupation is employment and who report either missing or zero wages and hours are not excluded. Instead the missing values of the hourly wage are coded as zero, and a dummy control variable for missing/zero values for wage and hours is included in all regressions with the hourly wage. The other control variables included in each model are age, age squared, female dummy, number of children, engaged in individual economic activity dummy, has an additional job dummy, rural dummy and region dummies. Unfortunately, information on industry is not available. In the restricted sample, all the characteristics of the individuals are measured in the base year, i.e. in 1992 for the first period and 1994 in the second period. The only information from the second round is the employment state of destination by ownership.

4 Results

4.1 Sample characteristics

Looking at the sample characteristics of those in state versus nonstate employment confirms that those in the two employment states differ in terms of their observable characteristics. Sample characteristics of those in state employment, nonstate employment and nonemployment in 1992 and 1994 are presented in Tables 3 and 4, respectively. The sample characteristics show that there is selection to state employment in terms of observable characteristics. As expected, the composition of those in the state employment in 1992 is similar to the composition of the employed population at the same time. However, the state employed are more likely to be university educated, female and to live in an urban area. In addition, they are less likely to engage in individual economic activity, to have wage arrears or zero working hours. Selection to state employment continues in the second period. In addition to being more likely to be female, and university educated those in state employment in 1994 are more likely to be in white-collar occupations. In both periods, the nonemployed are less likely to be highly educated and are clearly younger and more likely to be female. Thus the sample characteristics indicate that selection to state employment versus other employment is not random in terms of skill and education. These results confirm the findings of Gimpelson and Lippoldt (1999) about the composition of the two sectors.

In the main analysis of this paper I use the restricted sample to evaluate the determinants of leaving state jobs. The characteristics of those in the restricted samples in 1992 and 1994 are shown in the first column of Tables 3 and 4, respectively. There is some change in the composition of state employment over time. Compared to those in state employment in 1992, the state employed in 1994 are younger, have more children, are more likely to have university education, to engage in individual economic activity and not to be paid at all. The increase of those with wage arrears is remarkable but not surprising given previous evidence about the general increase in arrears around 1994. The increase in individual economic activity reflects an alternative survival mechanism that has been typical for Russia. In addition, the state employed in 1994 are less likely to have zero working hours and to live in an urban area or in the Moscow/St. Petersburg region. In addition to the urban/metropolitan effect there are large changes in the regional composition of the state employed.[7]

Finally, an increasing share of the state employed leave to nonstate employment or nonemployment within a year as shown in Table 5. In particular the share of those leaving state jobs to nonstate employment increases over time. This may partly reflect an increase in privatization activity in the second period. However, relative to those that stay the share of those who leave state jobs within a year is small.

4.2 Leaving state jobs

The main part of the analysis consists of estimating discrete choice models of leaving state jobs. I first investigate the determinants of leaving state jobs using the logit model. The results from logit models of leaving state jobs for the first period are shown in Table 6.[8] The results strongly support the hypothesis that those with poorest skills are more likely to leave state employment in the early part of the transition. In particular, those with university or special secondary education are less likely to leave state employment. The coefficients of the two variables are not significantly different.[9] Thus re-estimating the model after aggregating the two categories is a valid procedure. The resulting marginal effect of -0.058 (significant at 5 per cent) implies that having higher than general secondary education reduces the probability of leaving state employment

[7] The changes in sample characteristics of the state employed are verified by a two sample t-test of the sample means. The significant differences are: age ($p = 0.065$), number of children ($p = 0.047$), university ($p = 0.066$). For those engaged in IEA, those with no wage arrears, with nonzero hours, living in rural areas and regions the p-value is 0.000.

[8] A potential caveat for the multivariate analysis is high correlation between explanatory variables, which results in less accurate estimation of the model coefficients. Indeed, the level of pairwise correlation is relatively high for variables that measure skill, such as between supervisory responsibility and education categories. Somewhat surprisingly, the high correlation does not extend to the hourly wage. As a result, I estimate skill variables in separate models, controlling for the hourly wage.

[9] The pairwise Wald test for equality of the underlying coefficients is rejected for the other pairs of education categories: university to general secondary ($p = 0.005$), special secondary to general secondary ($p = 0.054$).

by 18 per cent. The negative education effect coincides roughly with the negative effect of supervisory responsibility. Having supervisory responsibility reduces the probability of leaving state employment by 14 per cent, slightly less than higher education. Finally, hourly wage has negative but insignificant effect in all models. The negative effect of the hourly wage controlling for education and/or skill is likely to reflect differences in productivity due to the quality of the job-worker match and unobserved ability.

The results for the second period are shown in Table 7. The results confirm the negative effect of skill proxies on the probability to leave state jobs with some important changes. In particular, the effect of skill proxies is weaker and more restricted. The effect of education is restricted to those with university education only.[10] However, the remaining negative effect is large, having university education reduces the probability of leaving state employment by 30 per cent. However, re-estimating the model using a single higher education category results in a marginal effect of the same magnitude as in period one. Although negative, the effect of supervisory responsibility is insignificant. The same is true for the hourly wage. The weaker effect of wages is likely to reflect the increasing importance of abnormal working conditions and payments.[11] Indeed, those that have a missing wage in the previous month are more likely to leave. For the second period the RLMS has information on occupations in addition to the above measures of skills. Thus, I re-estimate the model using white-collar occupation as a proxy for skills. Having a white collar occupation turns out to have a strong negative effect on the probability to leave state employment that is similar to the size of the effect of university education. This is consistent with results by Grosfeldt *et al.* (1999) from enterprise data, who find that white collar employment is

[10] The pairwise Wald test for equality is rejected for the pairs: university to special secondary ($p = 0.016$); university to general secondary ($p = 0.010$).

[11] Increase in nonpayment of wages and non-normal working hours is likely to increase mismeasurement in the hourly wage measure. However, using a monthly wage measure instead does not change the conclusions above. The monthly wage is positive but insignificant in all models.

less responsive to idiosyncratic shocks to firm's output.[12]

In addition to skill proxies, various control variables have a significant effect on the probability to leave state employment (not shown). In both periods age has a negative, quadratic effect with a turning point at around 40 years of age. This implies that among the working age population the young and those close to retirement age are more likely to leave state employment. Being female reduces the probability of leaving state employment in both periods. Regional patterns are important in the first period: living in an urban area and living in Moscow/St. Petersburg regions reduce the probability to leave state employment, while the effect of other regions varies. The effect of regions more or less disappears in the second period. In the second period, the emphasis shifts from regional differences to differences in non-normal compensation and outside activity. Those engaged in individual economic activity and those that do not receive a wage are more likely to leave. Having an additional job, however, does not have a significant effect on the probability to leave. Additional controls, such as payment in goods have a positive effect. The latter reflect the changing system of compensation and in particular the increasing importance of non-normal compensation practises in state firms, in determining the labor market outcome.[13]

[12] As an additional exercise, I include both occupation (8) and firm size (2) dummies as additional control variables. The predictive power of the models is significantly improved. However, with respect to the skill proxies, the overall conclusion of the results above remain. In addition, the occupation dummies turn out to be significant determinants of leaving the state sector. Somewhat surprisingly, firm size dummies do not have a significant effect.

[13] As an additional experiment, I estimate model (1) including subsidies from the enterprises to the household as an additional dummy in the first period. Surprisingly, subsidies have a small positive effect on leaving state employment (a marginal effect of 0.03 significant at 5%). According to this result enterprise benefits do not reduce the probability to leave state jobs. However, the measure of enterprise benefits is somewhat problematic. It is measured on the household level and does not accurately measure the compensation to the worker. Also, it includes all types of benefits provided by the firm, including diverse categories such as subsidized meals and housing. One potential explanation for the positive effect is simply that the enterprise benefits measure non-monetary compensation in failing firms.

The determinants of leaving state jobs seem to change between the two periods. In particular, there appears to be a general shift to more concentrated determinants of leaving state jobs in terms of the skill proxies. To formally evaluate the differences over time, I perform a pooled data test of stability of the results. I pool the data from the two periods and estimate the logit models above including a dummy for the first period and interactions of all variables with the first period dummy. It turns out that none of the interacted education or supervisory responsibility variables are significantly different from zero. This implies that it is not possible to statistically discriminate between the skill effects in the two periods. However, the poor predictive power of the models may reduce the power of the tests. Overall, there are enough differences in the two sets of results to consider the models unstable over time. This result is confirmed by likelihood ratio tests that clearly reject the homogeneity of the two results.[14]

The characteristics of those leaving state jobs to private employment are likely to be very different from those leaving to nonemployment. The logit model does not capture this difference. Thus I continue the analysis by estimating multinomial logit models with three destination states: state employment, nonstate employment and nonemployment, using the same model specifications as above. The results for the first period are presented in Table 8. The results confirm that higher education and supervisory responsibility have a negative effect on the probability to leave state employment irrespective of the destination state. Education continues to have a unified negative effect on the probability to leave for those that leave to nonemployment. The education effects are very large, they vary from a decrease in probability of 35 per cent for those with general secondary education to 45 per cent for those with special secondary education. In contrast, the effect of education is restricted to university education for those that leave to nonstate employment. All three education effects are statistically different across

[14] For a comparison of the fully interacted model and the model without interactions, the $\hat{A}^2$ values from likelihood ratio tests with 18 to 20 degrees of freedom range from 111 29 to 118 1 7.

nonstate and nonemployment equations.[15] Aggregating the two higher education categories results in marginal effects of -0.033 and -0.022 for nonstate employment and nonemployment respectively (both significant at 5 per cent). In contrast, the negative coefficients of supervisory responsibility are not significantly different from each other. Finally, hourly wage, although statistically insignificant, seems to have a more negative effect on transitions to nonstate employment rather than on transitions to nonemployment.

The effects of skill proxies are more limited and to some extent reversed in the second period. The results are presented in Table 9. Higher education continues to have a negative effect on transitions to nonstate employment. Having university education reduces the probability of leaving to nonstate employment by 35 per cent (compared to 15 per cent in the first period). Despite the nonsignificant marginal effect of special secondary education, the marginal effect of an aggregated higher education to nonstate is significant (-0.045, significant at 5 per cent). In contrast to the results of the first period, education does not seem to matter at all for transitions to nonemployment.[16] Supervisory responsibility has a weak negative effect for transition to nonemployment, but has no effect on transition to nonstate employment. Instead those with white-collar occupation are unlikely to leave state jobs to nonstate employment. The effect is relatively large, a reduction of 34 per cent in the probability to leave state employment to the nonstate employment. The

[15] In the nonstate equation, the pairwise Wald test for equality is rejected for the pair: university to general secondary ($p = 0.028$). In the nonemployment equation, the same test is rejected for the pairs: university to general secondary ($p = 0.072$) and special secondary to general secondary ($p = 0.028$). Across equations (eg. nonstate university to nonemployment university) the pairwise Wald test for equality is rejected for: university education ($p = 0.028$); special secondary education ($p = 0.000$) and general secondary education ($p = 0.027$).

[16] For transitions to nonstate employment the pairwise Wald test for equality is rejected for the pairs: university to special secondary ($p = 0.022$) and university to general secondary ($p = 0.011$). For transitions to nonemployment the same test is rejected for: university to general secondary ($p = 0.031$). Across equations the pairwise Wald test for equality is rejected for: general secondary education ($p = 0.096$).

effect is different from that of white-collar occupation on transition to nonemployment.[17] Contrary to the previous results, but consistent with logit results for the second period hourly wage is never significant.[18]

Consistent with logit results, control variables that are important determinants of leaving state jobs include age, sex, regions, non-normal compensation and outside activity (not shown). The strong age effect in the logit results remains valid for those leaving to nonemployment only. It appears that there is no evidence that those leaving to nonstate employment are more likely to be young and adaptable. Instead the young are more likely to experience nonemployment. In contrast, being female reduces the probability of transition to nonstate employment only. There is no sign of a significant difference between the sexes in the probability to move to nonemployment, which seems to imply a relatively strong attachment to jobs and the labor force for Russian females. Regions matter during the first period and to transitions to nonstate employment only. Living in an urban area has a strong negative effect, while other regions have significant coefficients with varying signs. As expected, failing to report positive working hours increases the probability of moving to nonemployment. Consistent with the increasing trend of arrears, not being paid in the previous month increases the probability of moving to nonemployment in the second period. In addition, being engaged in individual economic activity has a positive effect on the probability to move to nonstate employment in the second period. Having an additional job does not have any effect on the probability to leave. In all, it seems that engaging in outside activity does not seem to reduce the probability to leave state jobs.[19]

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[17] The pairwise Wald test for equality across equations is rejected ($p = 0.012$).

[18] Including occupation and firm size dummies reduces the significance of university education in the nonstate equation. Both occupation and firm size dummies are important in the nonemployment equation. In particular, working in a medium sized firm (101-1000 employees) reduces the probability to become nonemployed. Using the monthly wage instead of the hourly wage results in a weak positive wage effect for those moving to nonstate employment and weak negative effect for those moving to nonemploymnent.

[19] In addition, subsidies from the enterprise have a positive effect in the nonstate equation (0.049 significant at 5 per cent) and a negative effect in the nonemployment

To test the stability of the results over time I use the same pooled regression test as in the previous section. The only significant skill interaction terms are negative special secondary and general secondary interactions in the nonemployment equation. This result indicates that having any education above primary education reduces the probability of transition to nonemployment in the first period relative to the second period. Again the likelihood ratio tests reject stability of the results over time, suggesting that the pooled results themselves are not valid.[20]

As discussed above, the transitions to nonstate employment consist of both privatizations and true job moves from state to nonstate employment. It is thus possible that the results are driven entirely by the structure of privatization. Indeed, in the second period a majority, 71 per cent in the sample, of transitions to nonstate employment are privatizations that do not involve a job change. In order to evaluate the importance of privatization, I re-estimate the multinomial logit models using a separate state for privatized firms. The results, presented in table 10, show that the skill effect is partly due to the structure of privatization. Those with university or special secondary education are less likely to work in firms that are privatized. The changes in probability are relatively large and very significant. These results are confirmed by the large marginal effect of white-collar occupation for those in privatized firms. White-collar occupation reduces the probability of being in a firm that was privatized by 41 per cent. In summary, the results suggest that those with higher education or in white-collar occupations are more likely to stay in state firms because their firm is less likely to be privatized. Assuming that privatization results in restructuring, the weight on those with lower skills among the privatized movers suggests that the structure of the privatization process has contributed to the instability

equation (-0.018, significant at 10 per cent). The subsidies definitely hinder moves to nonemployment. This is not surprising, given that nonemployment in general is very undesirable. The positive coefficient for transitions to nonstate employment remains somewhat puzzling. It seems to suggest that the enterprise benefits function as a nonmonetary perk provided to best workers. However, the perk does not seem to increase attachment to state jobs.

[20] The χ^2 values with 36 to 40 degrees of freedom range from 164.90 to 177.47.

of low skill employment. For those that are making a real job move from state to nonstate jobs, education reduces the probability only for those with university education, by 38 per cent. This confirms that while the effect of privatization dominates, education does matter for job moves as well. Supervisory responsibility remains negative for those making a transition to nonemployment. This supports the suggestion that supervisory responsibility increases attachment to employment, irrespective of ownership type.

In addition to skill effects, various control variables have different effects on privatized and nonstate employment (not shown). As expected neither age nor sex matter for those in privatized firms. Those that are engaged in individual economic activity are more likely to be in firms that are privatized. This suggests that individual economic activity does not contribute to job search in the private sector. In addition, some regional differences persist in the structure of privatization. Contrary to those in privatized firms, those who make a real job move to nonstate employment are less likely to be female. After separating out those in privatized firms, a weak quadratic age effect re-emerges. These results suggest that in addition to a skill effect, females and those in their middle age are less likely to make a true job move to the nonstate sector.

5 Discussion

The results presented in the previous section show that the reallocation of labor from state to private jobs in Russia varies for different human capital and skill groups. Together with those in white-collar occupations and those with supervisory responsibility, the highly educated are also less likely to leave state jobs. The results have direct implications for the growth of the private sector, economic performance and loss of human capital during transition. Their importance, however, depend on the interpretation of the results. The results are potentially consistent with several stories of the reallocation of labor. Four stories seem particularly relevant: attachment, bad jobs, skill mismatch and privatization.

First, the results could be interpreted in terms of an attachment story. The attachment story is a favorite explanation of labor hoarding in general in Russia. In the context of this study, according to this interpretations workers with higher skills are for some reason more attached to state jobs than those with poorer skills. There are various potential reasons for attachment. One apparent reason is given by human capital theory that predicts that those with higher job-specific skills are less likely to separate in general. By definition such human capital is not transferable and is lost in the case of separation. However, the skill proxies used in the study are mostly measures of general rather than job-specific human capital. Further, job-specific human capital without some level of sector-specificity does not explain the results across employment states by ownership. Second potential reason for attachment is a higher level of nonpecuniary benefits in the state firm for those with higher skills. A significant share of Russian state firms provided social benefits such as housing, medical and childcare to their workers, while most private firms were unable to provide similar benefits. It has been argued that provision of social benefits has been used as a method to increase attachment and there is evidence that they are provided mostly to those at the top of the wage distribution (Kolev, 1998). Thus social benefits may have contributed to attachment. However, their importance is clearly decreasing as transition proceeds (see Commander and Schankerman, 1997). Finally, higher attachment to state firms could be explained by socio-cultural factors. Those with higher skills may be more likely to have socio-cultural reasons for higher attachment to the state job. These include ideology, socialist work ethic and job status.

Second, the results are potentially consistent with a bad jobs story. The bad jobs story implies that available nonstate sector jobs are predominantly low skill jobs and, as a result, there is a lack of demand for skilled labor in the nonstate sector. Indeed, because of overinvestment in heavy manufacturing during the socialist era, the transition to market involved a sectoral shift from manufacturing to services. Thus the nonstate jobs are proportionally more likely to be in service and craft occupations that are typical low-skill occupations. In addition, the prevalence of short time horizons is likely to result in small private R&D investment during transition, thus exacerbating the lack of demand for highly educated workers. However, the classification to good and bad jobs is not self-evident. Indeed, some new services such financial services, require relatively high skills. Unfortunately, there is little evidence about the quality of jobs across the two sectors. Two additional pieces of evidence based on wage evidence suggest that although nonstate jobs are predominantly low skill jobs they are not necessarily "bad" jobs. First, based on a ranking of occupations by earnings, monthly or hourly wages, the nonstate jobs are not only in the lower ranks. On the contrary, there are proportionally more senior managers, the highest earnings category, and less those in elementary occupations, the lowest earnings category, in the nonstate sector than in the state sector. Second, the earnings of those with higher education are relatively higher in the nonstate sector than in the state sector. For those with university education the nonstate to state wage ratio is between 1.2-1.3 in 1992 and 1.4-1.7 in 1994, while the same ratio for those with only primary education is 0.8 in 1992 and 1.2 in 1994, depending on the wage measure used.[21]

Third potential interpretation, skill mismatch, is closely linked to previous interpretations. However, instead of lack of supply or demand, the skill mismatch story implies a fundamental incompatibility of skills that exist in state jobs and skills that are demanded in nonstate jobs. In terms of human capital theory the mismatch story is an extension of specificity to sector-specific skills. It has been argued that narrow skills learned in the old educational system, in particular in vocational education, are poorly transferable to the new private environment (Boeri *et al.* 1998). In addition, the incompatibility of skills is likely to be a more serious impediment of mobility for high skill groups. An obvious example of such skill mismatch are market skills, such as modern management techniques. Indeed, skill mismatch in this category of workers was rec-

[21] The evidence presented here is rudimentary. In particular, a broader definition of good versus bad jobs that would include probability of wage arrears and short-time work, job security and nonpecuniary benefits would be needed for robust conclusions. In addition, multivariate methods would provide stronger evidence of both the ranking of good versus bad occupations and the education premium in the nonstate sector.

ognized early and training programs were designed to specifically target those with potential to fill the gap for management skills (OECD, 1995). Unfortunately, it is not possible to directly measure the extent of skill mismatch. However, the mismatch story seems to be roughly consistent with the wage evidence presented above.

Finally, the results show that there is a blue-collar bias in the structure of privatization. Blue-collar jobs are more likely to be privatized. Explaining this bias would require a study of corporate governance issues that are beyond the scope of this study. However, the bias towards blue-collar jobs in privatization could be partly explained by the industry structure of state jobs. The state sector includes education, health care and government administration sectors, which are likely to have a higher proportion of well-educated workers. In effect these sectors represent the portion of employment that is likely to remain state owned. However, the skill bias may also be a result of selective privatizations of production sectors with high skilled labor. Examples would include strategic energy industries, and industries that continue to supply the military.

The relative importance of each of these interpretations is unclear. However, it seems clear that the blue-collar bias in the structure of privatization constitutes a partial interpretation, particularly in the second period. The remaining negative effect to be explained is concentrated to those with university education. While the attachment story appears to be important in general, it seems less relevant for those with high levels of education. Thus the remaining stories, bad jobs and skill mismatch, appear to be the most likely explanations of the results.

In light of this interpretation the implications of the results seem particularly troubling. First, a direct implication is that the growth potential of the private sector is limited. It suggests that not enough emphasis has been put on policies that contribute to the quality of private employment. In addition, depending on the extent of skill mismatch, it may take some time before appropriate market skills are available. Second, the predominance of low skill jobs in the private sector is bad news for economic performance. Assuming that the nonstate sector jobs are more productive and allocate skills more efficiently, slow reallocation of human capital will results in lower labor productivity and output during transition. Indeed, it seems plausible that slow reallocation of human capital has already contributed to the poor output performance in Russia. In addition, to the extent that the private sector represents the future growth potential of the economy, the growth base of the Russian economy is limited by lack of appropriate human capital. Third consequence of the results is that an important resource, those with high general human capital, is not contributing to the transition. It also suggests that those with low skills end up shouldering most of short run microeconomic costs during transition. However, some of them are also more likely to reap the benefits of moving.

6 Summary

In this study, I have examined the determinants of leaving state jobs in Russia using representative household data, the RLMS. The results from various discrete choice models show that those with higher skills are less likely to leave state jobs. The negative effects are relatively large in some cases. In particular, having university education reduces the probability to leave state jobs to nonstate jobs by 15 to 38 per cent. Further, the negative effects depend both on the destination state and the time period. During the first years of transition, those with higher education and supervisory responsibility are less likely to leave state jobs. Later, those with higher education or in white-collar occupations are less likely to leave state jobs and particularly less likely to leave to nonstate employment. In the second period, most of the negative effect seems to be driven by a blue-collar bias in the structure of privatization. The results have implications for the growth of the private sector, economic performance and loss of human capital during transition. Given an interpretation based on bad jobs in the private sector, and skill mismatch the results have troubling implications for the Russian economy.

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Table 1. Structure of RLMS data and samples.

	Round 1	Round 3	Round 5	Round 6
Timing	07-10/1992	07–09/1993	11-12/1994	10-12/1995
Total N	16,641	15,037	11,284	10,648
Comparison N	9,320		6,165	
Full N	6,808		4,405	
Restricted N	4,436		1,994	

Notes:

1. Observations omitted in building the comparison sample due to (period 1, period 2): Attrition (3,110, 2,430), Missing/Conflicting data (3,604, 2,080), Not between 16-72 years of age (607,609).
2. Observations omitted in building the full sample due to: Not in working age, between 18-54(59 for men) years of age (2,512, 1,760).
3. Observations omitted in building the restricted sample due to: Not in state employment in base year (2,372, 2,411).

Table 2. Employment by ownership.

	1992	Goskomstat, 1992	1994	Goskomstat, 1994
State sector	81.6	69.8	62.4	45.8
Nonstate sector	18.4	30.2	37.6	54.2
N	5,319	na.	3,485	na.

Notes:

1. Authors calculations based on the comparison sample.
2. Goskomstat data from Table 1 in Gimpelson and Lippoldt (1999).

Table 3. Sample characteristics, 1992.

Variable	State	Nonstate	Nonempl.
Education categories:			
University	.20	.15	.12
Special secondary	.41	.40	.34
General secondary	.24	.25	.34
Primary	.15	.20	.21
Supervisory responsibility	.24	.22	-
Hourly wage (th R)	.02 (.04)	.02 (.04)	-
Control variables:			
Age	39.09 (9.66)	38.02 (10.06)	33.12 (12.36)
Female	.52	.40	.67
Number of children	1.04 (.96)	1.06 (1.02)	1.02 (1.00)
Has an additional job	.04	.03	-
Engaged in IEA	.02	.07	-
No wage arrears	.91	.83	-
Nonzero hours	.87	.81	-
Rural	.18	.36	.18
Regions:			
Moscow/St. Petersburg	.11	.10	.11
North/North East	.11	.11	.09
Central	.13	.15	.12
Volga	.11	.06	.10
North Caucasia	.17	.22	.21
Ural	.21	.10	.16
West Siberia	.05	.17	.08
East Siberia	.11	.08	.12

Notes:
1. Authors calculations based on the full sample.
2. Means, standard deviations in parenthesis.

Table 4. Sample characteristics, 1994.

Variable	State	Nonstate	Nonempl.
Education categories:			
University	.22	.18	.13
Special secondary	.40	.44	.34
General secondary	.23	.23	.31
Primary	.15	.15	.21
Supervisory responsibility	.23	.22	-
White-collar occupation	.45	.34	-
Hourly wage (th R)	1.34 (2.69)	1.54 (3.14)	-
Control variables:			
Age	38.61 (9.72)	37.56 (9.93)	33.60 (12.34)
Female	.52	.43	.60
Number of children	1.09 (.98)	1.06 (.96)	1.06 (1.11)
Has an additional job	.04	.05	-
Engaged in IEA	.06	.10	-
No wage arrears	.76	.75	-
Nonzero hours	.92	.90	-
Rural	.26	.22	.25
Regions:			
Moscow/St. Petersburg	.07	.10	.09
North/North East	.08	.08	.07
Central	.17	.19	.17
Volga	.20	.16	.16
North Caucasia	.11	.12	.17
Ural	.16	.16	.14
West Siberia	.10	.09	.11
East Siberia	.10	.09	.09

Notes:

1. Authors calculations based on the full sample.
2. Means, standard deviations in parenthesis.

Table 5. Transition probabilities.

Origin state	Destination states			
	State	Nonstate	Nonemployment	All
1992 to 1993:				
State	.727 $(3,224)$	.198 (877)	.076 (335)	1.00 $(4,436)$
1994 to 1995:				
State	.661 $(1,317)$	.257 (513)	.082 (164)	1.00 $(1,994)$

Notes:

1. Authors calculations based on the restricted sample.
2. Sample frequencies, number of observations in parenthesis.

Table 6. Leaving state jobs (logit model), 1992 to 1993.

	(1)	(2)
University	¡0.078	
	(¡3.24)	
Special secondary	¡0.054	
	(¡2.65)	
General secondary	¡0.028	
	(¡1.28)	
Supervisory responsibility		¡0.042
		(¡2.62)
Hourly wage (th R)	¡0.476	¡0.497
	(¡1.75)	(¡1.82)
Summary statistics:		
N	4436	4436
Wald χ^2(df)	228.83 (20)	220.34 (18)
Pseudo R^2	0.048	0.047

Notes:

1. The results are marginal effects calculated from logit coefficients. Robust t-statistics of coefficients in parenthesis.
2. The omitted education category is primary education.
3. The control variables included in each model are age, age squared, female, number of children, engaged in individual economic activity, has an additional job, nonmissing wage, nonzero hours, rural and region (7) dummies.
4. All characteristics are measured in the base year, 1992.

Table 7. Leaving state jobs (logit model), 1994 to 1995.

	(1)	(2)	(3)
University	¡0.117		
	(¡2.99)		
Special secondary	¡0.039		
	(¡1.12)		
General secondary	¡0.012		
	(¡0.33)		
Supervisory responsibility		¡0.034	
		(¡1.28)	
White-collar occupation			¡0.098
			(¡3.96)
Hourly wage (th R)	¡0.000	¡0.001	¡0.001
	(¡0.03)	(¡0.31)	(¡0.18)
Summary statistics:			
N	1994	1994	1994
Wald χ^2(df)	67.43 (20)	56.56 (18)	68.83 (18)
Pseudo R^2	0.027	0.022	0.028

Notes:

1. The results are marginal effects calculated from logit coefficients. Robust t-statistics of coefficients in parenthesis.
2. The omitted education category is primary education.
3. The control variables included in each model are age, age squared, female, number of children, engaged in individual economic activity, has an additional job, nonmissing wage, nonzero hours, rural and region (7) dummies.
4. All characteristics are measured in the base year, 1994.

Table 8. Leaving state jobs (multinomial logit model), 1992 to 1993.

	(1)		(2)	
	Nonstate	Nonempl.	Nonstate	Nonempl.
University	¡0.030	¡0.034		
	(¡1.81)	(¡3.30)		
Special secondary	¡0.006	¡0.041		
	(¡0.78)	(¡3.97)		
General secondary	0.006	¡0.028		
	(0.03)	(¡2.54)		
Supervisory responsibility			¡0.023	¡0.018
			(¡1.98)	(¡2.13)
Hourly wage (th R)	¡0.232	¡0.300	¡0.228	¡0.339
	(¡1.51)	(¡1.03)	(¡1.54)	(¡1.19)
Summary statistics:				
N	4436		4436	
Wald χ^2(df)	391.97 (40)		376.45 (36)	
Pseudo R^2	0.068		0.065	

Notes:

1. The results are marginal effects calculated from multinomial logit coefficients. Robust t-statistics of coefficients in parenthesis.
2. The omitted education category is primary education.
3. The control variables included in each model are age, age squared, female, number of children, engaged in individual economic activity, has an additional job, nonmissing wage, nonzero hours, rural and region (7) dummies.
4. All characteristics are measured in the base year, 1992.

Table 9. Leaving state jobs (multinomial logit model), 1994 to 1995.

	(1)		(2)		(3)	
	Nonstate	Nonempl.	Nonstate	Nonempl.	Nonstate	Nonempl.
University	¡0.099	¡0.008				
	(¡3.11)	(¡0.84)				
Special secondary	¡0.049	0.012				
	(¡1.49)	(0.38)				
General secondary	¡0.038	0.029				
	(¡0.95)	(1.18)				
Supervisory responsibility			¡0.010	¡0.023		
			(¡0.68)	(¡1.69)		
White-collar occupation					¡0.106	0.007
					(¡4.60)	(¡0.24)
Hourly wage (th R)	0.001	¡0.002	0.003	¡0.016	0.001	¡0.002
	(0.15)	(¡0.65)	(¡0.12)	(¡0.74)	(0.08)	(¡0.68)
Summary statistics:						
N	1994		1994		1994	
Wald χ^2(df)	121.94 (40)		106.39 (36)		123.85 (36)	
Pseudo R^2	0.035		0.036		0.037	

Notes:

1. The results are marginal effects calculated from multinomial logit coefficients. Robust t-statistics of coefficients in parenthesis.
2. The omitted education category is primary education.
3. The control variables included in each model are age, age squared, female, number of children, engaged in individual economic activity, has an additional job, nonmissing wage, nonzero hours, rural and region (7) dummies.
4. All characteristics are measured in the base year, 1994.

Table 10. Leaving state jobs (multinomial logit model), 1994 to 1995.

	(1)			(2)			(3)		
	Privatized	Job move	Nonempl.	Privatized	Job move	Nonempl.	Privatized	Job move	Nonempl.
University	¡0.070	¡0.027	¡0.008						
	(¡2.74)	(¡1.96)	(¡0.83)						
Special secondary	¡0.063	0.010	0.012						
	(¡2.16)	(0.41)	(0.39)						
General secondary	¡0.013	¡0.024	0.029						
	(¡0.43)	(¡1.39)	(1.19)						
Supervisory resp.				0.004	¡0.013	¡0.024			
				(¡0.17)	(¡1.14)	(¡1.70)			
White-collar occ.							¡0.096	¡0.007	0.007
							(¡4.79)	(¡1.22)	(¡0.24)
Hourly wage (th R)	0.001	0.001	¡0.002	¡0.001	0.001	¡0.003	0.001	0.001	¡0.003
	(0.10)	(0.25)	(¡0.65)	(¡0.34)	(0.37)	(¡0.74)	(¡0.05)	(0.37)	(¡0.78)
Summary statistics:									
N		1994			1994			1994	
Wald χ^2(df)		173.32 (60)			146.68 (54)			164.43 (54)	
Pseudo R^2		0.045			0.040			0.045	

Notes:

1. The results are marginal effects calculated from multinomial logit coefficients. Robust t-statistics of coefficients in parenthesis.
2. The omitted education category is primary education.
3. The control variables included in each model are age, age squared, female, number of children, engaged in individual economic activity, has an additional job, nonmissing wage, nonzero hours, rural and region (7) dummies.
4. All characteristics are measured in the base year, 1994.

A Empirical methodology

The logit model is a standard tool in the estimation of models with a binary dependent variable. The basic difference to linear regression is a distributional assumption that results in predicted probabilities that lie between 0 and 1. As a result the model is estimated using the maximum likelihood method.

Specifically, the binary choice model is based on an underlying unobserved variable y_i^* that varies across individuals $i = \{1, 2, ..., N\}$. The underlying variable is defined as: $y_i^* = x_i'\beta + \varepsilon_i$. It consists of a systematic component $x_i'\beta$, where x_i are the characteristics of the individual, and a random component ε_i. The random component is assumed to be distributed logistically with $E(\varepsilon_i) = 0$.[22] The choice based on the underlying variable can be represented by a binary variable:

$$y_i = \begin{cases} 1 & if \quad y_i^* > 0 \\ 0 & if \quad y_i^* \leq 0 \end{cases} . \tag{1}$$

The probability of a move is given by: $P(y_i = 1) = P(y_i^* > 0) = \Lambda(x_i'\beta)$, where $\Lambda(.)$ is the logistic cumulative distribution function. The logit model is estimated by maximum likelihood. The log likelihood is:

$$\ln L = \sum_i [y_i \ln P_i + (1 - y_i) \ln P_i] \tag{2}$$

The first derivative is:

$$\frac{\partial lnL}{\partial \beta} = \sum_i [y_i - P_i]\, x_i, \quad \forall j = 1, 2, ..., J \tag{3}$$

The logit coefficient represents the effect of a change in the independent variable on the log-odds. The marginal effect is:

$$\frac{\partial E(y_i)}{\partial x_i} = [P_i(1 - P_i)]\, \beta \tag{4}$$

[22] It is possible to interpret the underlying variable as the unobserved utility of an employment state. The choice of employment state then is made based on utility maximization, and decision to leave is taken once a threshold for utility in the destination state is above the utility in the original state.

Notice that for dummy variables the marginal effect refers to an effect on the probability of a change from 0 to 1. The goodness of fit of the logit model is evaluated using the pseudo-R^2 derived from the likelihood ratio and the likelihood ratio test of restricting all slope coefficients to zero (Greene, 1998). The predicted probabilities reported in the study are calculated using the method of recycled predictions. The method involves calculating the predicted probability for each subgroup using the whole sample instead of only the subsample in question. For example, in calculating the predicted probability for those with university education, I use the characteristics of the whole sample instead of only those with university education. The differences in predicted probabilities then give the difference due to university education holding other characteristics of the sample constant (for discussion see pp. 406-407 in Stata Corporation, 1999).

The multinomial logit model is a generalization of the logit model to multiple states with an additional assumption of independence between the states. The errors of the underlying variable are assumed to be independently and identically distributed with a Weibull distribution.[23] Then the probability of choice k for individual i and a set of choices $j+1 = \{0, 1, 2, ..., J\}$ is:

$$P(y_i = k) = \frac{e^{\beta_k' x_i}}{\sum_{j=0}^{J} e^{\beta_j' x_i}} \tag{5}$$

In order to identify the coefficients a normalization is necessary. This is achieved by setting $\beta_0 = 0$, i.e. estimating probabilities with respect to a base category. With this normalization, the probabilities are:

[23] The Weibull distribution is given by: $F(\varepsilon_{ij}) = \exp(e^{-\varepsilon_{ij}})$. The undesirable side-effect of the assumption is the irrelevance of the third choice when a choice between two states is made, the so-called Irrelevance of Independent Alternatives (IIA) assumption. Clearly, the IIA assumption is a priori unacceptable in the case of choice between employment states. However, since the multinomial logit method is here used for descriptive purposes only this problem is set aside.

$$P(y_i = k) = \frac{e^{\beta_k' x_i}}{1 + \sum_{j=1}^{J} e^{\beta_j' x_i}}, \quad \forall j = 1, 2, ..., J \tag{6}$$

$$P(y_i = 0) = \frac{1}{1 + \sum_{j=1}^{J} e^{\beta_j' x_i}} \tag{7}$$

The multinomial logit model is estimated by maximum likelihood. The log likelihood is:

$$\ln L = \sum_i \sum_{j=0}^{J} d_{ij} \ln P_{ij} \tag{8}$$

Where d_{ij} is an indicator that takes on values 1 or 0 if alternative j is chosen. The first derivative is:

$$\frac{\partial lnL}{\partial \beta_j} = \sum_i \left[d_{ij} - P_{ij}\right] x_i, \quad \forall j = 1, 2, ..., J \tag{9}$$

The estimation of an multinomial logit model results in coefficient estimates β_j for each choice relative to a base category. The marginal effects are given by:

$$\frac{\partial E(y_{ij})}{\partial x_i} = P_j \left(\beta_j - \sum_j P_j \beta_j \right) \tag{10}$$

Goodness of fit measures and the method of calculating predictions are the same as for the logit model above (Greene, 1998).