Essays on Occupational Social Class and Status in Post-Soviet Russia

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Abstract

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The aim of this thesis is to explore several aspects of occupation-based inequality in post-Soviet Russia that have previously been given little attention in the literature. The data sources for statistical analysis are the Russian Longitudinal Monitoring Survey (RLMS) and the International Social Survey Programme (ISSP). Various statistical techniques have been used, such as regression models with random and fixed effects, nonparametric and semiparametric regression models, survival models and log-multiplicative models for contingency tables.

First, the thesis looks at the validity of the application of the European Socio-Economic Classification (ESeC) in Russia. The results show that ESeC classes in Russia are different in respect to several aspects of their employment contract, such as the probability of informal employment, the index of fringe benefits and unemployment risks. This confirms the validity of the ESeC for Russia.

Second, the association between earnings and age is analyzed. The shape of cross-sectional age-earnings profiles in Russia is different from the shape in Western countries, especially for men. There is little variation in earnings across age groups, and younger men have higher average earnings than older men. The thesis suggests and discusses several explanations for this, such as age segregation in the labour market and the effect of class structure.

Third, the thesis explores the class gap in mortality. Non-manual classes have lower mortality risks than manual classes, both for men and women. The size of the class gap in mortality in Russia is larger than in Western European countries.

Fourth, the thesis constructs an occupational status scale and analyzes its properties. The scale is based on the information about intermarriages between occupational groups. The Russian scale is similar to the scales previously constructed for European countries and the USA.

Overall, the thesis demonstrates similarity in the patterns of occupation-based inequality in Russia and in Western industrial countries. It also discusses some technical aspects of class analysis and suggests a more clear separation between the descriptive and causal logic within it.

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Chapter 1

Introduction

The study of Russia makes an interesting case for social scientists. Russia is usually not considered to be one of the developed "first world" countries. By many parameters, such as GDP per capita, life expectancy or the level of corruption, Russia is substantially different from most Western states. On the other hand, few people would consider Russia to be one of the "developing" countries. GDP per capita and the proportion of urban population are larger in Russia compared to India, China and most other countries of Asia and Africa (but comparable to Brazil, Argentina or Turkey).

Russian political and social thought has been preoccupied with the question of the place of Russia in the world at least since the 19th century. The points of view varied. Some people considered the country to be essentially part of Western civilization and constantly insisted on the economic and political reforms that would make Russia more European. Others argued that Russia should follow its own historical path, and that the basic values and the structures of social life in Russia are very different from Western countries. This ideological debate among Russian intellectuals has been central to modern Russian history and has strongly affected political decisions.

What makes the Russian case even more interesting is the experience of socialism that the country underwent in the 20th century. The Russian revolution of 1917 aimed to create a society organized in a completely different way when compared with the capitalist Western nations. For most of the 20th century, Russians lived in an economy without market institutions and with very limited private property. The socialist experiment eventually failed, but it has left a trace in people's attitudes and societal institutions. The subsequent post-Soviet double transition to a market economy and a political democracy was unprecedented. Contrary to the plans and hopes of the Russian reformers, the political and economic institutions that resulted from the transition did not always resemble the Western states.

This leaves us with a simple question: to what extent are social and economic structures and processes in contemporary Russia similar or different to those of Western Europe and the USA? While there is a substantial variation within the European countries and the USA, they undoubtedly share some common features. Are those features also characteristic for Russia?

Descending from this quite high level of abstraction, we can specifically address the question of social stratification. Much research has been conducted in Western countries, particularly in the US and the UK, on class inequality, the effects of social background on educational aspirations and achievement, social mobility, inequality in the labour market, occupational prestige and other topics traditional for the studies of social stratification. Surprisingly, the research in this field – and especially quantitative research – on Russia is quite limited, even compared with China, not to mention Western countries. In particular we lack comparative studies.

In this thesis, I deal with occupational class and status in Russia. As will be clear from the following review of the literature, this is an area where our knowledge on Russia is especially limited. I address the question of whether the class schema, usually applied in quantitative research of social stratification in Western countries, is valid in the case of Russia. I apply this class schema to study the variation in employment contracts, unemployment risks, age-earnings profiles and mortality. I also construct an occupational status scale for Russia and check its validity.

The only way to assess the pattern and magnitude of occupation-based inequalities in Russia is to compare them with other countries. While this thesis mainly deals with only one country, Russia, I do compare the results for Russia with published results for other countries, mainly Britain and the USA.

Thus, the contribution of this thesis to the social stratification literature consists of two parts. First, by validating the occupational class and status measures for Russia it provides a methodological basis for further research on social stratification in Russia. Second, it addresses several substantive questions and compares the patterns and magnitude of occupational inequalities in Russia and Western countries.

In this introduction I first provide a review of the studies of social inequality in the USSR and post-Soviet Russia. I describe the characteristics of the labour market in Russia, discuss existing research on income, educational, gender and class inequalities and identify a gap in the literature that this thesis aims to fill. Then I provide a thesis outline with a more detailed discussion of the content of each chapter. Finally, I describe the data sources that were used in the thesis.

1.1 Social inequality in the USSR

The socialist ideology of the Soviet state strongly disapproved of social inequality. According to the official dogma, there were no antagonistic classes in the USSR and the life chances of different social groups were equalized. The reality was, of course, quite different. As in any other modern society, social inequality did exist in the Soviet Union.

However, it is much harder to make conclusions about the degree of inequality in the USSR than in Western states. The reason is the scarcity of data available for quantitative analysis. The social sciences in the USSR remained under strict ideological control, and research on many topics was either forbidden altogether or severely restricted. National surveys were not conducted until the late 1980s. In the late 1960s and early 1970s Soviet sociologists produced several interesting studies of social inequality, but these were based on local samples that make it harder to generalize the results to the entire population. Besides, the results were published mainly in the form of descriptive secondary statistics that often precluded further analysis. The Western scholars of Soviet society did not have access to data collection and mostly had to rely on secondary, incomplete, Soviet sources.

Despite these difficulties, some conclusions could be made. Bergson (1984) analyzed income inequality under Soviet socialism and concluded that it was smaller than in most capitalist countries, although to a lesser extent than previously thought (also see Yanowitch (1977) and Connor (1979)). The difference in the level of income inequality was greater if the Soviet Union was compared with countries with a similar level of economic development. Although it is even harder to make reliable conclusions about the dynamics of income inequality during the Soviet period, available evidence suggests that it decreased in the first decade after the revolution of 1917, then dramatically increased during the period of Stalin's rule and decreased again in the 1960s and 1970s (Bergson, 1984; Dobson, 1977), thus following the Kuznets curve.

Katz (1997) studied the gender gap in wages in the USSR with the microdata from a local survey conducted in Taganrog, a town in the south of Russia, in 1989. The results showed that the gender wage gap was comparable in size with those reported for European countries. Women in the USSR earned about 30% less than men. Many women were concentrated in professional occupations (such as physicians and teachers) with reduced working hours and, as a result, higher hourly wages.

Income inequality does not really capture the degree of inequality in consumption in the USSR where the economy was to a large extent non-monetary. Access to many goods was regulated and limited to certain groups in the population. Fringe benefits played an important role in job remuneration. Matthews (1978) and Voslensky (1984) provided interesting evidence of the privileges enjoyed by the Soviet political and cultural elite, based on the qualitative interviews and, in the latter case, personal experience.

The Soviet studies of occupational prestige conducted in the 1960s showed that the occupational hierarchy in the USSR was largely similar to Western countries (Yanowitch and Dodge, 1969; Treiman, 1977). However, some minor differences existed, with skilled manual workers ranked higher and sales and services workers ranked lower than in the West. I provide a more detailed review of these studies in chapter 6.

Despite the repeated attempts of the Soviet state to equalize educational opportunities of different social groups, children with more privileged social backgrounds had higher educational achievement. Educational inequality in the USSR was consistent with the hypothesis of maximally maintained inequality (MMI) (Raftery and Hout, 1993): inequality at the lower educational levels persisted until educational opportunities at these levels expanded and then inequality was transferred to the higher educational levels. The rapid growth of secondary education in the USSR in the 1950s and 1960s created a "bottleneck" at the entry to university level where children with advantaged social background enjoyed higher transition rates (Gerber and Hout, 1995).

As educational inequality is one of the major mechanisms for the intergenerational transmission of social advantage, it is not surprising that similar findings apply to intergenerational social mobility. Both early studies based on secondary statistics from the local Soviet surveys and later studies based on retrospective information collected in the national surveys confirmed that parents in the Soviet

Union passed on their social advantage to children, although social mobility was perhaps somewhat higher in the post-WWII USSR than in Western states (Gerber and Hout, 2004; Dobson, 1977; Yanowitch, 1977; Connor, 1979). In the 1920s and 1930s social mobility was even higher (Fitzpatrick, 1979), although it is hard to quantify it.

Overall, the nature of social inequalities observed in the USSR was quite similar to those of Western societies. Both income and educational inequality existed and social advantage was passed from parents to children, although the degree of income inequality and social immobility was somewhat smaller than in the West. These similarities are perhaps common features of all industrial societies, even if they are very different in other respects, such as political systems (see, for example, Inkeles and Rossi, 1956, for an early development of this argument).

On the other hand, the mechanisms for creating inequalities, at least in the economic sphere, were very different in socialist and capitalist societies (Goldthorpe, 1966). In the West the market played the central role in creating and maintaining inequalities, while in socialist societies inequalities were the result of state redistribution policies. This created some types of inequalities that were not characteristic of the West. For example, the Soviet state always favoured heavy industries rather than light industries and services. Workers who were employed in the military complex and selected industrial enterprises were paid more and had better fringe benefits then workers in other industries and enterprises (Katz, 1997; Gerber and Hout, 1998).

The collapse of the USSR in 1991 and the Russian transition to a market economy had dramatic consequences for the nature and extent of social inequality in Russia. These developments are reviewed in the next section.

1.2 Transition to a market economy and social inequality in post-Soviet Russia

The post-Soviet economic and social transformation in Russia can be roughly divided into two periods. After the "shock therapy" of the price liberalization introduced by the Russian government in early 1992, economic conditions rapidly deteriorated. In 1992 inflation reached more than 2,500 percent. Between 1992 and 1994 GDP contracted on average by 12% every year (Brainerd, 1998; Gerber and Hout, 1998). Industrial production contracted by half (Gimpelson and Lippoldt, 2001). Compared to the late Soviet period, the living standards of Russians dramatically declined. Income and consumption per capita were both decreasing from 1992 to 1998 (Gorodnichenko et al., 2010).

At the same time, the period from 1992 to 1998 witnessed important economic reforms. Trade was liberalized. Most enterprises were privatized in the course of the rapid mass privatization programme that began in 1993. By the end of 1994, 65% of enterprises in Russia were privatized (Gerber and Hout, 1998). Self-employment was rising, although at a slower pace than originally expected. The labour market, only rudiments of which existed in the USSR, has emerged.

In 1998 Russia was affected by a major financial crisis. The Russian currency was devalued, inflation increased again, income and consumption considerably declined (Gorodnichenko et al., 2010). However, after 1998 an economic recovery began, stimulated by the devaluation of the ruble and fueled by rising oil prices. From 1999 to 2008 Russia's GDP increased by 82% and income per capita increased by about 250% (in constant prices). The number of people with money incomes below the poverty line decreased from 42.3 mln (29% of Russia's population) in 2000 to 18.9 mln (13.4%) in 2008 (Rosstat, 2010). After the beginning of the world financial crisis in 2008 the economic growth stopped and in 2009 GDP contracted by 8%. However, this was not accompanied by a cutback in the population's incomes.

The period of economic and social decline (1992-1999), usually associated with the presidency of Boris Yeltsin, is markedly different from the period of economic recovery (2000-08) that coincided with the presidency of Vladimir Putin. In this section I will review the dynamics of economic and social inequality in Russia in these two periods.

1.2.1 The emergence of the labour market in Russia and its characteristics

In the USSR resources and benefits were allocated administratively by the state. Despite this, some mechanisms that resembled developed labour markets existed. Workers were free to change jobs, and enterprises competed for the labour force, offering fringe benefits within the limits established by the state (Clarke, 1999). However, by and large the labour market emerged in Russia only with the destruction of administrative barriers in the beginning of the 1990s. Since then the labour market has become one of the major mechanisms of the production of economic and social inequalities.

The expectations of the architects of the Russian market reforms were that the "shock therapy" would cause a rapid reallocation of the labour force. Initially, ineffective Soviet enterprises were expected to dismiss workers, contributing to the rise of unemployment. As the market reforms progress and the economy recovers, successful firms would hire available workers, thus completing the reallocation of the labour force according to the needs of the new market economy.

The reality, however, was different to what was expected. Perhaps one of the most characteristic features of the Russian labour market in the 1990s was that the radical market reforms did not produce mass unemployment (Gimpelson and Lippoldt, 2001; Kapeliushnikov, 2001). The reaction of most enterprises to the deep economic crisis and industrial decline of the 1990s was not to dismiss workers, but to reduce their pay. This task was made simpler by high inflation, so that managers did not have to reduce nominal salaries, but simply failed to keep up to the growth of prices. Another instrument for adjusting to the crisis was wage arrears and sending workers on unpaid leave. The arrears peaked in 1998 (Gerber, 2006), the year when incomes and consumption were also at their lowest (Gorodnichenko et al., 2010).

At the same time, despite a prolonged industrial decline many industrial enterprises in the 1990s continued to actively hire workers. Their goal was often not to dismiss a redundant labour force, but to replace employees who were leaving voluntarily, dissatisfied with low salaries (Clarke, 1999, ch.2). On the other hand, new jobs were created, mostly in services, and people did use these opportunities for occupational mobility. About 42% of employed Russians changed their occupation between 1991 and 1998, that is about twice more than in 1985-91 (Sabirianova, 2002). Sabirianova (2002) showed that between 1985 and 1998 the number of service workers and managers considerably increased, while the number of industrial workers and engineers decreased. Much occupational mobility was downward: workers moved down to the occupations that did not require high educational qualifications and the occupations with a lower average wage. During the economic growth of the 2000s occupational mobility in Russia remained high (Maltseva and Roschin, 2006).

One of the characteristic features of the Russian labour market has been the difference between the private and public sectors of employment. In the USSR, private employment *de facto* did not exist (although many agricultural enterprises were formally owned by the workers). After the rapid mass privatization programme of the 1990s, most Russian enterprises were privatized and remained either in private or mixed (state and private) ownership. Besides, new private enterprises emerged, especially in finance and services, with jobs that were usually of higher quality. The pay in the private sector was higher than in the state sector, although workers in state enterprises enjoyed higher job security (Clarke and Kabalina, 2000).

An important feature of the labour market in post-Soviet Russia was wage differentiation at the firm level. Standard inputs in earnings regression equations (such as sex, age, education, occupation, industry, region, sector of employment) fail to explain more than about 50% of the variance in earnings (Gimpelson and Kapeliushnikov, 2007). In other words, workers with the same observed characteristics could have very different earnings, depending on some unobserved factors. Scholars who studied the Russian labour market agree that these factors most likely operated at the firm level (Clarke, 1999; Gimpelson and Kapeliushnikov, 2007). Economically successful firms paid their employees more than firms that experienced financial problems. In the highly insecure and unstable economic environment of post-Soviet Russia, especially in the 1990s, the fortunes of firms could change quickly. This stimulated high job mobility and, as a consequence, the returns to firm-specific experience in Russia were low. The most successful employees often changed jobs, always ready for new opportunities.

Summarizing, the new Russian labour market operated in a chaotic environment that only became more stable with the economic recovery of the 2000s. Despite the forecasts, the market reforms of the beginning of the 1990s did not bring mass unemployment. Firms reacted to the economic crisis by reducing real salaries and wage arrears that peaked in 1998. Being employed did not necessarily mean getting paid, and salaries were often below the subsistence level. This caused a dramatic decline in the living standards of most Russians. As a result of the privatization and liberal reforms, private sector and self-employment emerged, with earnings higher than in the state sector. Industry rapidly declined, while the service sector was on the rise. With the economic fortunes of firms rapidly changing, interfirm occupational and job mobility was high. The economic growth of the 2000s improved the situation. Incomes and consumption went up, and the problem of wage arrears was largely solved. However, interfirm mobility remained at a high level.

In the next two subsections I discuss how these developments affected economic and social inequality in Russia. I start with earnings and income inequalities. Then I move to the inequalities in educational attainment and health, and also look at the social advantage of former Communist party members. Finally, I review the literature on class inequality and intergenerational social mobility.

1.2.2 Earnings inequality in post-Soviet Russia

After the collapse of the USSR income inequality in Russia skyrocketed. Gorodnichenko et al. (2010) provide the following estimates, based on the data from the Russian Longitudinal Monitoring Survey (RLMS) (see a review in section 1.4.1). In 1985 the Gini coefficient for earnings was 0.28, in 1990 – 0.32, but in 1995 it increased to 0.48. The 50/10 ratio went up from two to four between 1990 and 1995, a fact that shows a rapid deterioration of the economic situation of the poorest people. According to Brainerd (1998), between 1991 and 1994 wage inequality in Russia nearly doubled.

After 1994 wage inequality in Russia remained relatively stable. The Gini coefficient for average monthly earnings was 0.48 in 1994, then it somewhat decreased between 1994 and 1998, increased again between 1998 and 2000, and after 2000 went down and reached 0.41 in 2005. The 50/10 ratio decreased in 1996 compared to 1994 and 1995, then remained stable and decreased again after 2002. To summarize different inequality measures, wage inequality remained stable after 1994 and decreased after the beginning of the economic recovery in 2000. Similar trends were observed for household income, expenditure and consumption (all the estimates are taken from Gorodnichenko et al. (2010)).

What were the factors underlying the dynamics of income inequality in post-Soviet Russia? The market transition theory, developed by Nee (1989, 1991, 1996) on the basis of the analysis of economic reforms in China, predicts that the transition to a market economy should cause an increase in the returns to human capital. According to this logic, the socialist state equalized the earnings of workers with different education and skill levels and the transition to the market principles of work remuneration should increase inequality between those groups.

Whether this indeed happened in the early period of the transition (1991-94) is debatable. Gerber and Hout (1998) analyzed the data from five Russian surveys conducted in 1991-96 and did not find an increase in the returns to education. They also noticed that the returns to human capital were low in Russia compared to Western countries. On the other hand, Brainerd (1998) showed with data for 1991-94 that came from the same polling firm in Russia that the returns to education increased in 1993 and 1994 compared to 1991. Gorodnichenko et al. (2010) demonstrated with the RLMS data that the education premium did not change significantly in 1994-2005. For all this period, the average hourly wage of university educated men was about 1.5 times higher than for non-university educated men (apart from 2002-2003 when this ratio seems to be somewhat larger, about 1.7).

The decrease of earnings inequality in the 2000s can be accounted for by the fall of the unexplained residual variance component in the household earnings equation that included year, age, location, education and household composition (Gorodnichenko et al., 2010). In other words, the decline in earnings inequality should be explained by something other than all these factors. This can be a reduction of the occupational wage differentials or the firm-specific differences in pay between workers with the same qualifications. The question of what exactly explains the decrease of earnings and income inequality in Russia in the 2000s remains open and requires further research.

The destruction of the social security safety nets of the socialist state increased poverty. Lokshin and Popkin (1999) concluded on the basis of the RLMS data for

1992-96 that only a small percentage of the Russian poor were persistently below the poverty line and most of them moved in and out poverty. Families headed by single parents and families with more than two children were especially likely to be poor. On the other hand, pensioners, commonly believed to be among the victims of the market transition, were much less likely to be persistently poor. The reason is perhaps small, but regular state pensions could still be larger than salaries in some enterprises, especially when the latter were not paid on time.

Another new phenomenon for post-Soviet Russia was homelessness. It is very hard to estimate reliably the number of homeless people in Russia and, in general, to study homelessness quantitatively. The homeless are not represented in the surveys where samples are based on household rosters. Stephenson (2006) cited the estimates by the Institute of Socio-Economic Problems of the Russian Academy of Science and the results of an unpublished survey conducted by the Ministry of Interior in 2002. According to these estimates, there were about 4 mln homeless people in Russia. This is most likely to be a gross exaggeration based on a very broad definition of homelessness (defined as not being registered with the state at a particular place). More conservative estimates by the Ministry of Interior that looked at street homelessness showed that there were only about 15,000 homeless people in Moscow and 8,000 in St.Petersburg. However, in both cities homelessness, almost unfamiliar or at least well hidden in Soviet times, suddenly became very visible.

Gender wage inequality remained stable from 1994 to 2005. On average, men earned about 1.7 times more than women if measured in monthly earnings, and about 1.4 more if measured in hourly wages (Gorodnichenko et al., 2010). Women were less likely to be employed in the private sector and more likely to be employed in the low-wage industries (Gerber and Mayorova, 2006). They were less occupationally mobile than men. On the other hand, women were less likely to be laid off, and unemployed women had better chances of finding a job (Gerber and

Mayorova, 2006).

An interesting fact about inequality in Russia is the difference in earnings across age groups. Contrary to Western countries where men in their 40s and 50s had the highest average earnings, in Russia men in their 30s were the most economically privileged (Brainerd, 1998; Gerber and Hout, 1998; Gimpelson and Kapeliushnikov, 2007; Gorodnichenko et al., 2010). In 2006 the age of maximum average earnings for Russian men was 33. For women the tendency for younger workers to earn more than their older colleagues was weaker, and the distribution of average earnings across the age groups was closer to Western countries. Most economists who looked at this problem hinted at the differences in human capital across the cohorts. I review this literature in detail in chapter 4 and suggest alternative explanations.

Interestingly, Guriev and Zhuravskaya (2009) found substantial differences in the distribution of life satisfaction across the age groups between market transition countries (including Russia) and non-transition countries. In the non-transition countries the youngest (in their 20s) and the oldest people were most satisfied with their lives. In the transition countries, life satisfaction monotonically decreased with age. Young people in the transition and non-transition countries had approximately the same level of life satisfaction, but in older cohorts average life satisfaction was much higher in the non-transition countries. As Brainerd (1998) summarized, "the "winners" from this transformation – at least in the short period under study here – are young well-educated men whose skills have enabled them to exploit new profit-making opportunities in the private sector of the economy. The losers are older workers, men in particular, whose human capital has been devalued and who have few incentives to acquire new skills relevant to the emerging economy".

We can add to this summary that the "winners" mainly lived in big cities, especially Moscow and St.Petersburg, while the "losers" often resided in the countryside and outside big metropolitan areas. If earnings inequality in a Mincer-type earnings regression is decomposed into parts, location and gender would explain the largest parts of the total variance (while, for example, age does not matter much) (Gimpelson and Kapeliushnikov, 2007). In 2005 monetary income per capita in Moscow was 10.4 times higher than in the republic of Ingushetia, the poorest Russian region (although this gap diminishes if we account for the differences in consumer prices) (Gorodnichenko et al., 2010).

1.2.3 Inequalities in educational attainment and health. Former Communist party members in post-Soviet Russia

Education is one of the major factors to affect earnings, other labour market outcomes and life chances in general. Social scientists who study social inequality have been long interested in the intergenerational transmission of educational achievement. It is well known that children from more educated families have better chances to obtain higher educational qualifications. Gerber and Hout (1995) showed that this was also true for the USSR, despite the periodic attempts by the Soviet government to reduce educational inequalities.

In the first half of the 1990s the Russian educational system experienced some contraction, both at the levels of academic secondary and tertiary education (Gerber, 2000a). Male enrollment in the universities declined, although female enrollment did not change. Gerber (2000a) showed that the decline of enrollments in academic secondary schools disproportionately affected children with lower origins (measured by parents' education and occupation). At the level of tertiary education, the effect was less clear and the changes in the transition probabilities of students with different social backgrounds were minor and ambiguous.

Starting from the middle of the 1990s, enrollment in Russian universities increased. New private universities emerged. How these developments affected educational inequalities has not been studied.

Gerber (2000a) also found that children from the families of former members of the Communist party were more likely to make educational transitions both at the level of academic secondary and tertiary education. A large literature deals with the advantages of former Communist party cadres and members in post-socialist countries. Kryshtanovskaya and White (1996) analyzed the composition of the new Russian elite and documented that most of its members already held powerful positions in the USSR. Rona-Tas (1994) showed that former communist cadres kept their privileged positions during the market transition in Hungary. Gerber (2000b) demonstrated that not only former Communist cadres, but even ordinary Communist party members had higher earnings in post-Soviet Russia than non-members, both in 1993 and 2000 (Gerber, 2001b).

What exactly explains the advantage of the former Communist party members in post-socialist countries is debatable. Rona-Tas (1994) emphasized the institutional inertia that allowed Communist party members to transmit their advantage to a new social context using their social capital (also see Rona-Tas and Guseva, 2001). Gerber (2000b, 2001b) suggested that the advantage of former party members can be explained by some unobserved characteristics (such as their ambition and opportunism). It is quite plausible that these personal qualities increased the probability of joining the party in Soviet times as well as promoted success in the post-Soviet period.

Another subject that is important for understanding social inequalities in post-Soviet Russia is health inequality. The market transition in Russia was accompanied by a dramatic decline in life expectancy, especially among men. Rising alcohol consumption was perhaps the most important factor that affected the deterioration of the health of Russians (Leon et al., 2007, 2009). However, the increase in mortality rates in the post-Soviet period was unequal. People with low educational qualifications suffered the most, while the life expectancy of people with university degrees actually increased (Shkolnikov et al., 1998b; Plavinski et al., 2003; Murphy et al., 2006). The gap in mortality between the groups with the highest and lowest levels of education widened.

There are at least two explanations for this. The social and economic developments and the alcohol crisis in Russia could affect particularly badly the health of the least educated people (who occupied less advantageous positions in the labour market), while the effect on well-educated people could have been not so devastating. On the other hand, one should take into account the differences across the cohorts in educational achievement that were a consequence of a rapid increase in enrollments to universities in the USSR in the 1960s. In the oldest cohorts, higher education was a rare privilege and most people only had secondary or vocational diplomas. In the youngest cohorts, the proportion of people with a university degree is much higher. Thus, the widening mortality gap between educational process can be potentially explained by demographic processes.

I review the literature on health inequality in Russia in more detail in chapter 5.

1.2.4 Social class inequality

There are not many empirical studies of social class inequality in contemporary Russia. By social class here and elsewhere in the thesis I mean occupation-based social class, measured according to the Erikson-Goldthorpe (EGP) or similar class schemes. This is the definition that is almost universal now in the studies of social stratification. In labour economics, the field in which most of the research on the labour market and income inequality in post-Soviet Russia has been conducted, the concept of class is not usually applied. Public health experts often use education or broadly defined socio-economic status as a measure of social position, and only rarely apply the class schemes. Most published research on occupational social class in Russia has been done in sociology by Theodore Gerber and Michael Hout.

Gerber and Hout (1998) analyzed the class structure and class inequality in earnings in Russia between 1991 and 1996 (with class operationalized according to the EGP schema). Within this period, the class structure remained relatively stable, with the largest classes being professionals, lower routine non-manual and skilled and unskilled manual workers. Self-employment was emerging only slowly, with proprietors constituting under 2% of all employed people. The proportion of professionals slightly decreased between 1992[1] and 1996, while the proportion of routine non-manual employees somewhat increased.

In terms of earnings, self-employed proprietors were the most advantaged class, and their earnings rose continuously from 1991 to 1996 (also see Gerber, 2001a, 2004). The self-employed were followed by managers. Unskilled manual workers, skilled manual workers in the private sector and lower routine non-manual workers had the lowest earnings. The earnings of professionals were quite low, compared to their counterparts in the West. In fact, in the first half of the 1990s professionals in the private sector had approximately the same salaries as skilled manual workers in the state sector.

Bian and Gerber (2008) revisited the same problem with the data for 1984-2001[2] and compared the class structure and class-based earnings inequality in urban Russia and China. For the purpose of comparability, the Russian samples included only urban areas. The analysis of the class structure in Russia was conducted separately for men and women. Self-employment became more widespread in the second half of the 1990s and by 2001 reached 7% among urban men and 3% among urban women. The proportion of skilled manual workers contracted, from 43% in 1984 to 33% in 2001 for men and from 17% to 12% for women. A similar contraction happened among semi- and unskilled workers. On the other hand, the proportion of routine non-manual workers rose both among men and women.

[1] The data for 1991 were limited to European Russia and strictly speaking were not comparable with other years.

[2] The data for 1984 and 1988 for Russia were retrospective.

The dynamics of the Russian class structure reflected a shift from the industrial economy of the late USSR to the more service-oriented economy of post-Soviet Russia in the 1990s.

Bian and Gerber (2008) also analyzed class differences in earnings in Russia from 1993 to 2002 (retrospective data on earnings for the earlier period were not available). The analysis was conducted jointly for men and women. As in the earlier analysis (Gerber and Hout, 1998), proprietors and managers had the highest earnings, and unskilled manual and routine non-manual workers were the poorest. There was no discernible trend in class-based earnings inequality in Russia in 1993-2001.

Gerber and Hout (2004) studied intergenerational class mobility in the USSR and post-Soviet Russia. They concluded that the association between origins and destinations tightened in post-Soviet Russia compared to the Soviet period. The mechanism was downward occupational mobility of men with lower-class origins. This is consistent with Sabirianova (2002) who found significant downward occupational mobility during the transition period.

In all these studies Gerber, Hout and Bian used a modified version of the EGP class schema that separated managers from professionals. Both the EGP schema and its modifications are discussed in detail in chapter 2.

Another line of research examined the class patterns in voting in Russia. Evans and Whitefield (2006, 1999) analyzed the survey data on voting intentions in 1993-2001 and established that the salariat was more likely to vote for the pro-market right-wing parties and candidates while the working class was more likely to support left-wing interventionist politicians. The class effect was crystallizing over time. Evans and Whitefield explained this by political learning (also see Evans, 2006). The class-based differences in voting intentions were statistically significant, but not particularly strong, especially compared with the effect of age.

In an unpublished paper Evans and Whitefield (2003) checked the validity of the EGP class schema in Russia with the data from a series of surveys conducted in 1993-2001. They established that, in line with Goldthorpe's class theory, occupational classes were different in terms of their employment contracts in the same way as in Britain. Managers and professionals were less likely than manual workers to be paid overtime, more likely to be on monthly rather than hourly pay, had higher work autonomy and better job prospects (see Chapter 2 for a discussion of the class-relevant characteristics of employment contracts). Evans and Whitefield (2003) also investigated class-based differences in income, consumption and self-identity.

Finally, there are a number of studies of the "middle class" in Russia. In most cases, the "middle class" in these studies is defined by income, education, assets or some combination of these factors. The operationalization of class in these studies is very different from the EGP class schema or other occupation-based class schemes applied in quantitative sociology. See Maleva (2003) for a review and an example of this type of study.

1.3 Thesis outline

As shown in the previous section, the research on social class in Russia remains quite limited in scope. One of the issues that has received little attention in the literature is the validity of the application of the EGP class schema in Russia. While the EGP class schema and its successors were validated for Western European countries (Evans, 1992; Evans and Mills, 2000; Rose et al., 2003; Rose and Harrison, 2010), Poland and Hungary (Evans and Mills, 1999), this has not been done for Russia (with the exception of the unpublished paper by Evans and Whitefield (2003)). Most of the research on Russia that uses the EGP operationalization of class is based on the assumption that it is applicable to Russia to the same extent as to Western countries.

The same is true for the other major tradition in social stratification research that uses occupational scales instead of categorical class schemes (see Chapter 6 for a review of this approach). No occupational scales were constructed with the Russian data, and the validity of the application of the international occupational scales in the Russian context has not been tested.

In this thesis I deal with two related issues. First, I check the validity of the EGP class schema (or, more precisely, its successor, the European Socio-Economic Classification) to Russia. To do this, I look at the class differentials in employment contracts, age-earnings profiles and mortality. I also construct and validate an occupational status scale for Russia. From this point of view, the thesis can be seen as an exercise in the validation of the occupation-based measures of social position in Russia.

Another way to look at the empirical studies presented in the thesis is to emphasize their substantive rather than methodological side or, in other words, to focus on dependent rather than independent variables. From this point of view, the thesis contributes to the understanding of the determinants of informal employment contracts, fringe benefits, unemployment and mortality risks and to the analysis of social inequality and labour market outcomes in post-Soviet Russia.

The thesis consists of one introductory, one theoretical and four empirical chapters that aim to explore different aspects of occupational stratification in Russia. The thesis is structured as follows.

In chapter 2 I review the theories of social class applied in contemporary quantitative sociology and describe the theoretical foundations of John Goldthorpe's class theory. Then I discuss the differences between descriptive and causal approaches to class analysis and introduce a modelling strategy applied in the thesis. Finally, I analyze the differences between three methods to code EGP class.

Chapter 3 investigates the differences in employment contracts between classes in Russia. First, I analyze changes in the class structure in Russia between 1994 and 2006, separately for men and women. Then I look at the existing class differences in the probability of informal employment contract, in the number of fringe benefits and in the unemployment risks. To account for the panel structure of the data, I use both random- and fixed-effects estimators.

Chapter 4 analyzes the shape of age-earnings profiles in Russia and the class differences in age-earnings profiles. In Russia, contrary to Western European countries, relatively young men earn more than older men. The class differences in age-earnings profiles were previously used to validate the EGP class theory and schema (Goldthorpe and McKnight, 2006). I look at the class-specific age-earnings profiles in Russia to check if the theory holds. The methodological contribution of this chapter is in using nonparametric regression models to account for the non-linearity of the association between age and earnings.

Chapter 5 looks at the patterns of class inequality in mortality in Russia. Previous research on the inequalities in mortality in Russia analyzed the differences between educational groups. I use a range of epidemiological techniques (such as calculation and standardization of mortality rates, calculation of life expectancies, Kaplan-Meier analysis and Cox models) to establish class-based patterns in mortality in Russia, separately for men and women. Then I look at the effect of class mobility and perceived social status on mortality.

In chapter 6 I construct an occupational status scale for Russia using the relational approach to the scale construction based on the data on the occupations of marital partners. In order to do this, I apply log-multiplicative models for contingency tables. Then I discuss the properties of the scale, validate it and compare it with international occupational scales.

In Conclusion I summarize the results of the empirical chapters and discuss their implications for social stratification research in general and the study of social inequality in Russia in particular.

1.4 Data sources

The empirical analysis in the thesis is based on the statistical analysis of the survey data. In this section I review the data sources that were used in the analysis.

The major data requirement for the analysis of occupational class and status is the availability of the information on respondents' occupation, coded in detail (usually at the level of four- or three-digit International Standard Classification of Occupations or a similar national classification). The major survey that fulfills this requirement is the Russia Longitudinal Monitoring Survey (RLMS) that constitutes the basis for the empirical analysis presented in most of the chapters.

1.4.1 The Russia Longitudinal Monitoring Survey

The RLMS is perhaps the most widely used survey in the studies of inequality and labour market behaviour in Russia.[3] This is a household panel survey conducted in Russia annually since 1992 (except 1997 and 1999). The description of the data in this section follows the information provided on the RLMS website (RLMS, 2010).

The study consists of two major phases. The panel for the first phase of the RLMS was formed in 1992. The sampling procedure was based on the three-stage stratified cluster sampling. Twenty primary sampling units and 200 secondary sampling units were selected. For round I, conducted in 1992, 7,200 households were targeted, of which 6,334 provided the data (88.8% response rate). The data were collected via face-to-face interviews by the Russian Statistical Office. In 1992-93 four rounds of the survey were conducted.

In 1994 a new phase of the study began that included the construction of a completely new sample. As I mainly use the data from phase II, I discuss it in more detail.

[3] I thank the Russia Longitudinal Monitoring Survey Phase 2, funded by the USAID and NIH (R01-HD38700), Higher School of Economics and Pension Fund of Russia, and provided by the Carolina Population Center and Russian Institute of Sociology for making these data available.

Contrary to phase I, the sample in phase II was based on a larger number of primary sampling units. First, 2,029 administrative regions of Russia were divided into 38 strata of a roughly equal size, on the basis of the geographical factors, the level of urbanization and ethnicity. Remote regions of the North and Far East and Chechnya were removed from the list. After that procedure, 1,850 administrative regions remained that represented 95.6% of the Russian population. Three larger strata were included in the final sample with certainty: Moscow city, Moscow region and St.Petersburg. In the remaining 35 strata, one administrative region was sampled within each region, according to the probability proportional to size principle. Therefore, 38 primary sampling units were selected.

The target sample size in round 5 (the first round of phase II) was set to 4,718 households. The sample excluded the institutionalized population. Each PSU was divided into urban and rural sub-strata. The target sample size was split between urban and rural sub-strata, proportional to their size in the PSU. In rural areas, villages constituted secondary sampling units (SSU). Then one village was selected for each ten households in the rural sub-stratum of the PSU. Within each village, 10 households were selected from the household list.

In urban areas, the 1989 census districts were taken as the SSUs. For each 10 households one district was selected, according to the probability proportional to size principle.

Each household in the sample was visited up to three times in order to secure an interview. The most knowledgeable member of the household answered questions from a household questionnaire. All other adult members of the household completed an individual questionnaire. Children were not interviewed; the information about them was obtained from adults.

The response rate at the household level was 87.6% in round 5, 82.1% in round 6 (compared to the original sample), 79.4% in round 7, 77.7% in round 8, 75.3% in round 9. Non-response was higher in the cities, in particular Moscow and

St.Petersburg, rather than in the countryside. Due to the high non-response rate in Moscow and St.Petersburg, in 2001 the sample for these two cities was replaced with a completely new sample. Hence, in round 10 the response rate compared to the original 1994 sample was low, 57.9% (but it was 80.3% for the sample outside Moscow and St.Petersburg). The response rate was 57.3% in round 11, 54.8% in round 12, 54.3% in round 13 and 50.8% in round 14. In round 15 (2006) new households were added in big cities to repair the sample. Thus, the response rate in round 15 went down to 44.9% (50.6% for the comparable parts of the sample).

If a family from the original sample moved somewhere else, the organizers tried to follow the family to the new address (within the same PSU). However, the new family at the original address was also interviewed. Therefore, the data for each round of the RLMS consist of two samples. The cross-sectional sample includes all the households found at the addresses in the original sample, but does not include the households that changed address. The longitudinal sample includes the households that were in the original sample, but does not include new families that were found at the addresses in the original sample. In round 5 (1994) cross-sectional and longitudinal samples are the same.

Data collection in phase II was performed by the Institute of Sociology of the Russian Academy of Science. In most analyses, I use the data for the years from 1994 to 2006.

The questionnaires in the RLMS included a wide range of questions about household composition, budget and consumption, as well as questions about the individual labour market situation and experiences, income, health, attitudes, etc. Most importantly for us, there were detailed questions about individual occupation and employment status that allowed to code the occupational class and status of respondents.

The RLMS is perhaps the best available source of microdata on the labour market, inequality and health in Russia. The panel structure of the data set is particularly important as it allows us to address research questions that would not be possible to study with simple cross-sections (such as, for example, inequalities in mortality). The data were collected according to a transparent and clear protocol, with a relatively low non-response rate. Of course, there are also shortcomings. The most disadvantaged groups of the population most likely had a lower response rate that can bias the results. The response rate in Moscow and St.Petersburg was low compared to the rest of the country. The sample was constructed in 1994 with the household lists available at that time, and it does not take into account new dwellings built since 1994 (although for Moscow and St.Petersburg the sample was re-sampled in 2001). However, even taking into account all these constraints, usual in survey research, the RLMS is a reliable data source, frequently used in academic research on Russia.

1.4.2 The International Social Survey Programme

The analysis in chapter 6 is mainly based on the data from the Russian part of the International Social Survey Programme (ISSP). The reason for this is that the construction of an occupational status scale requires a large sample, and as the ISSP is a cross-sectional survey this can be achieved by pooling the data for different years. As well as the RLMS, the ISSP records the occupation of respondents according to the four-digit ISCO classification that makes it possible to code occupational status groups.

Russia has been taking part in the ISSP annually since 1992. The data collection was performed by the Levada Centre, a polling organization. Here I describe the characteristics of the survey in 2004 (as specified in the codebook); the characteristics for other years were similar.

One hundred and seventy six PSUs were selected in 35 strata, defined by seven administrative macro regions and five types of rural and urban settlements within each macro region. Moscow, St.Petersburg and all cities with a population of over

500,000 people were selected automatically. In other strata, PSUs were selected with a probability proportional to the size of the PSU.

To select SSUs, electoral districts were used. In the cities with a population of over 500,000, one SSU was chosen for each four or five interviews. In other PSUs, two SSUs were randomly chosen from the list. In total, there were 410 sample points.

The households were selected with the random route method. Each household was visited up to four times at different times and on different days of the week. If after four visits the contact with a respondent was not established or they refused to participate, the next door address was visited. Within the households, respondents with the nearest birthday to the visit date were selected.

The total eligible sample size was 6,082. Out of this number, 1,800 questionnaires were received, which makes a 29.6% response rate. Most of the non-response was due to non-contact rather than refusals. Admittedly, the non-response rate in the Russian part of the ISSP is quite high. However, I only use the ISSP to construct a contingency table of the occupations of marital partners and check the validity of the resulting occupational status scale. Most of the other analyses are based on the RLMS.

1.4.3 Other data sources

To construct age-earnings profiles for 1991 (i.e., the period before the beginning of the market reforms in Russia) in chapter 4, I use the data from the General Social Survey - USSR (ICPSR 6500). This survey was conducted in the European part of the USSR in April-May 1991 by Michael Swafford in cooperation with the Institute of Sociology of the Academy of Sciences of the USSR (Swafford et al., 1995). The sample included the permanent population aged over 18. The sample size was 2,521, with the response rate over 84%. Since the sample represented the European part of the USSR and included the Ukraine, Belorussia and Lithuania (but did not include Siberia and the Far East), it is not strictly speaking comparable with the latest Russian surveys. Since I only use this survey to construct two age-earnings profiles that, besides, are not central for the argument in chapter 4, I omit further details.

What other surveys could be used in the study of social stratification in Russia? Since 2005, Russia has been taking part in the European Social Survey (ESS). So far the data for two ESS rounds (2006 and 2008) are available for Russia. However, the range of questions on labour market behaviour and employment contracts is smaller in the ESS when compared to the RLMS. Moreover, the RLMS has a larger sample size and the advantage of being a panel survey. Compared to the ISSP, the Russian part of the ESS gives a smaller sample size for the pooled sample.

The Russian Socio-Economic Transition Panel (RUSSET) is a panel survey conducted from 1993 to 1999 by a consortium of Dutch universities[4]. Compared to the RLMS, this survey has a smaller sample size and, besides, it is an individual rather than a household panel. The RUSSET project was stopped in 1999.

In 2003 the World Bank conducted the National Survey of Household Welfare and Participation in Social Programmes (NOBUS), with its main objective being to evaluate social assistance programmes in Russia. Data collection was completed by the Russian Statistical Office. An advantage of the NOBUS is its large sample size (44,529 households and 117,209 individuals). However, occupation in the NOBUS was coded in a very broad way that does not allow to code occupational class and status according to the standard procedures.

The Russian Statistical Office regularly conducts the Labour Force Survey, quarterly since 1999 and monthly since 2009. The sample size is about 70,000 respondents. Occupation is coded according to the Russian Occupational Classification, compatible with the ISCO. Unfortunately, primary data from the Labour Force Surveys are not available to researchers.

[4]See `http://www.vanderveld.nl/russet.html`

There are also a number of other surveys conducted by Russian polling firms, but none of these surveys can match the RLMS in terms of the sample size, data quality and the range of questions. The combination of the RLMS and ISSP is the best possible data option for the goals of this thesis.

1.5 Methods and software

In this thesis I use several statistical methods of data analysis. Since the methods applied in each empirical chapter are different, they are described in detail in the methodology sections of the respective chapters.

The statistical analysis was conducted with Stata 9.1 and R. Some models in chapter 6 were estimated with ℓEM. Plots were created in Stata and R.

Chapter 2

Theory and Operationalization of Occupational Social Class

Social class is one of the central concepts in sociological theory and empirical analysis. But despite its popularity, there is no commonly agreed definition of what social class actually means and how it should be measured. I begin this chapter by giving a brief outline of different approaches to class analysis, focusing on those that are most often used in modern quantitative sociology. Then I discuss in more detail the Erikson-Goldthorpe (EGP) class schema, the modification of which is used in the thesis. The next section of the chapter describes the differences between causal and descriptive class analysis and introduces the modelling strategy that I subsequently apply in empirical analysis. Finally, I compare and discuss different ways to operationalize EGP class, using Russian data to illustrate the differences between them.

2.1 Concepts of social class in empirical quantitative research

In Marxist social theory classes were defined according to their position in the system of production and ownership of the means of production. Classes were seen as antagonistic and, therefore, engaged in either potential or actual class conflict. This theory was hugely popular and influential for most of the 20th century, but in its original and unmodified form has few supporters now, at least in the academic community.

Weber discussed the concept of class in only two short papers in "Economy and Society", but this discussion has become one of the most well-known topics in sociology, disseminated in numerous textbooks. Contrary to the Marxist tradition, he rather broadly defined classes in relation to the economic life chances that their members possess in the labour or commodity markets, without any reference to exploitation or antagonistic interests. In Weber's view, social status, as opposed to class, is determined in the sphere of consumption rather than production and is manifested with different life styles.

Various versions of Marxist and Weberian class analysis were proposed in the 20th century. However, many of these theories operated at the grand theoretical level and only a few offered operationalizations of class that can be applied in empirical research based on survey data. The aim of this section is not to give an exhaustive review of all or even most of the well-known sociological theories of class, but instead to describe those theories that were applied and validated in quantitative empirical research and justify the choice of the class schema that is used throughout the thesis.

The operationalization of class that is perhaps most often applied in empirical research is the Erikson-Goldthorpe class schema (also known as the EGP schema). It was produced in the course of cross-national research on social mobility (Erikson et al., 1979; Erikson and Goldthorpe, 1992) in order to create an internationally comparable measure of class. The EGP schema differentiates between several groups of workers, from higher managers and professionals to non-skilled manual workers, on the basis of their occupation, employment and supervisory status. The assumption of the schema is that the class of individuals is based on their position in the labour market. Depending on the level of detail, the number of classes in the EGP schema may vary from three to eleven.

The theoretical foundation for the class schema was developed by Goldthorpe in his later work (Goldthorpe, 2000). It is based on the ideas from transaction costs economics that relate the type of employment contracts in different occupational groups to the nature of the job performed. (In section 2.2 I review Goldthorpe's theory of social class in more detail.) Members of the occupational groups that have the same type of employment contract are in the same labour market situation that affects their labour market outcomes (Goldthorpe and McKnight, 2006), political preferences (Evans, 1999), health, etc.

Another empirical approach to class analysis is represented by the neo-Marxist class schema created by E.O.Wright (Wright, 2005). Wright sees exploitation as the central element of class relations. Empirically this schema is based on measuring property relations, authority and expertise in the work place. Coding class according to Wright's schema requires more information than using the EGP schema and this information is not readily available in most surveys. Perhaps this is the reason why the EGP schema has been more often applied in empirical research. Besides, despite different theoretical bases, empirically the EGP and Wright's class schemes are not very far from each other.

Recently Grusky, Sorensen and Weeden suggested another approach to class analysis that intends to replace "big" classes that are present in both EGP and Wright's class schemes with the analysis at the level of much smaller occupational groups (Grusky and Sorensen, 1998, 2002; Grusky and Weeden, 2001; Weeden and Grusky, 2005; Weeden et al., 2007; Jonsson et al., 2009). This approach is different from more conventional EGP class analysis in the following respects.

First, Grusky, Sorensen and Weeden argue that conventional big classes fail to capture occupational heterogeneity within classes. In the last two decades many sociologists have claimed that social class is no longer a good predictor of individual-level outcomes and that these outcomes depend on other characteristics, such as personal tastes and identities (the argument known as the "death of class", see Pakulski and Waters (1996)). The proponents of the microclass analysis suggest that this is not the case; however, in order to modernize traditional class analysis big classes should be replaced with a much more detailed occupational schema. Weeden and Grusky (2005) show that a more detailed occupational schema does explain more variability in life chances, life styles, political and social behaviours and dispositions than either traditional class schemes or occupational scales.

Second, microclasses are "real" social groups, while big classes are largely "nominal" groups. It is argued that big classes are academic constructs designed to capture the differences in employment contracts (or authority relations) between occupational groups that the members of these groups may not be explicitly aware of. In contrast to this, belonging to particular occupations is usually associated with some occupational identity. In other words, people know that they are doctors or welders, but are not aware that they belong to the classes of higher managers and professionals or skilled manual workers. There are social closure mechanisms that operate at the occupational level in the form of self-selection to particular occupations by people with specific values and attitudes, occupational training, social interaction within the same occupation and similar working conditions (Weeden and Grusky, 2005).

Third, according to the logic of microclass theorists, members of narrowly defined occupations can act collectively, extracting occupational rent and protecting their interests (Grusky and Weeden, 2001). Contrary to this, the theoretical logic of the EGP schema implies that members of the same class have similar economic interests, but do not necessarily act collectively to advance them.

Despite certain advantages that the analysis at the detailed occupational level offers, there is also a major practical disadvantage. It requires samples that are much larger than those that are often available for quantitative social research. Weeden and Grusky (2005) use the occupational scheme with 126 categories and validate it with pooled General Social Survey data and data from the US Current Population Survey. There are no publicly available data sets for Russia with sample sizes that would support the analysis at this level of detail. While I admit that looking at separate occupations rather than aggregating big occupational classes in the context of the labour market dynamics in post-Soviet Russia would be an interesting research enterprise, present data constraints make its practical implementation impossible. The same is true for Wright's class schema; none of the data sets that I use in the thesis contain information that would allow me to code it.

Partly for these practical reasons, throughout the thesis I use the EGP class schema. Besides, the fact that the EGP schema is the most popular in contemporary quantitative sociology facilitates a comparison of results for Russia with other countries.

Two further points should be made before we move to the discussion of the EGP class theory in more detail. First, apart from aggregating occupations in classes, sociologists often construct hierarchical occupational scales. This is an entirely different tradition in social stratification research that I do not review in this chapter, but describe in chapter 6.

Second, in other social science disciplines the concept of social class has been less popular than in sociology. Economists do not use the concept of class, focusing instead on education and income or earnings. In public health literature researchers often apply the concept of socio-economic status (SES), operationalized in a variety of ways at the individual or aggregate levels in cases when only aggregate-level data are available. The operationalization of SES can be based on education, income, asset ownership, occupation, unemployment or poverty status, or some combination of these variables. EGP class is used sometimes, but without much attention given to the theoretical basis of the schema.

2.2 John Goldthorpe's theory of social class and the EGP class schema

The EGP class schema derives class from a position of individuals in the labour market. First, it differentiates between proprietors and employees. As most people in contemporary societies are employees, this distinction alone leaves a researcher with a group that is too large to be usefully applied in empirical analysis. Further distinctions between employees that the EGP schema makes are related to the types of employment contracts they have.

In the analysis of employment contracts, Goldthorpe borrows some analytic tools from the economic theory of transaction costs. Employers determine the type of employment contracts of workers according to two main criteria. The first criterion is job specificity, or, in other words, to what extent a job requires specific skills and, as a consequence, longer on-the-job training. When a job requires specific skills, it is costly for employers to replace workers, as new employees will require a longer period of training. Therefore, employers are more likely to keep workers with specific skills for a longer period of employment.

The second criterion is the degree to which work and its results can be easily monitored and controlled. When work can be easily monitored, as is the case with many manual occupations, the incentive system for workers is rather straightforward. Their pay depends directly on productivity when it can be measured, or time spent at work. However, in occupations where direct monitoring is not possible, employers have to create more complicated incentive schemes, such as career ladders with regular promotions.

Using these two dimensions (job specificity and the ease of monitoring), Goldthorpe differentiates two main types of employment contract. The first type, the service relationship, implies that job skills are specific and it is hard to monitor the work process and its results. In this case, employers are more interested in long-term relations with employees, as their replacement is costly. The service relationships are characterized by the salary as a form of payment that is not directly associated with productivity, career ladders that strengthen employees' attachment to the firm, and more job autonomy. According to Goldthorpe, this type of employment contract is most often used for managers and professionals.

The second type of employment contract is the labour contract that is mainly used in manual occupations. In this case, job specificity is low and the results of work can be directly measured. Workers are paid according to their productivity or the time they spend at work. Work autonomy is low and prospects for promotion via career ladders are limited.

These are two "ideal types" of employment contract that Goldthorpe defines. There are also mixed forms of contracts when job specificity is high, but monitoring and control is easy, or the other way round.

Using the distinction between proprietors and employees, and the types of employment contracts, the full version of Goldthorpe's class schema defines eleven classes. Classes I and II are higher and lower managers and professionals with a service relationship with employers. Class IIIa consists of higher routine non-manual workers with a mixed form of employment contract (low job specificity combined with higher job autonomy). Class IIIb contains lower routine non-manual workers with a labour contract. Classes IVa, IVb and IVc are self-employed, with employees, without employees and in agriculture, respectively. Class V contains manual supervisors, with the mixed form of employment contract that combines higher job specificity and lower job autonomy. Classes VI, VIIa and VIIb are manual workers with the labour contract. Class VI consists of skilled workers, class VIIa contains semi- and non-skilled workers, and class VIIb is semi- and non-skilled workers in agriculture.

The eleven-class schema can be contracted to nine, seven, five or three classes, depending on the level of detail necessary in the analysis and the constraints imposed by the data.

Goldthorpe's class theory has been repeatedly reviewed in the literature. A more detailed discussion is available elsewhere (Goldthorpe, 2000; Breen, 2005; Rose and Harrison, 2010).

Before discussing practical use of EGP classes in section 2.4, I describe the modelling strategy applied in this thesis, as it differs from the one that is often used in quantitative class analysis.

2.3 Causal and descriptive logic in class analysis

Class analysis, like any other statistical analysis in the social sciences, can be performed in two ways, the descriptive and the causal. The difference between these two approaches is sometimes blurred in the sociological literature. The aim of this section is to clarify it and describe the modelling strategy for the subsequent statistical analysis.

2.3.1 Class as a causal concept

At the theoretical level, class as operationalized by the EGP schema is undoubtedly a causal concept. Members of the same class have similar employment contracts, and this affects their position in the labour market, their economic perspectives and security (Goldthorpe and McKnight, 2006). The theoretical mechanism here implies causality: members of different classes have different life chances *because* of the occupational differences in employment contracts.

Causality is a complex concept that has been defined in many different ways in the history of science and statistics (for a brief historical review see Pearl, 2000, pp.331-358). Many (but not all) scholars agree that it is impossible to derive statements about causal relationships between two phenomena (or, in the statistical language, two variables) from observational data alone. Some theoretical model is required that explicitly defines causal mechanisms that relate one phenomena to the other. In some natural sciences, these theoretical models take the form of scientific laws that deterministically define how exactly one variable would change as a consequence of the change of another variable.

In the social sciences, the deterministic concept of scientific laws is not applicable. Regularities observed in the social world are probabilistic. Still the logic remains similar. Recently, several scholars underlined the importance of a detailed understanding of the mechanisms that bring about the statistical association between two variables for making causal inferences in social science (Goldthorpe, 2001; Hedstrom, 2008). For example, to show that class affects unemployment risks, one must not only establish the statistical association that would satisfy the statistical criteria for causality, but also provide a detailed description of the mechanism that shows precisely how and why class membership affects unemployment.

This approach to causality is based on the explanation of how the actions of individuals bring about social outcomes of interest. Goldthorpe (2001) suggests that it is the most appropriate approach for sociology. According to Goldthorpe, it is different from the counterfactual approach to causal inference, developed and widely accepted in statistics.

The counterfactual approach to causal inference, developed mainly by Donald Rubin and also known as the Neyman-Rubin model, is described in detail elsewhere in the sociological literature (Morgan and Winship, 2007; Gangl, 2010). Briefly, it is based on the analysis of the effect of an actual or hypothetical intervention (the treatment) on the outcome variable. For the same unit, the outcome can take two values, under treatment and control conditions. The fundamental problem of counterfactual causal inference is that the outcomes for the treatment and control cannot be observed at the same time for the same unit. Hence, researchers can only estimate average treatment effects that are the difference between the outcomes under the treatment and control conditions for two groups.

The key condition for unbiased estimates of causal effects is ignorability, i.e. the independence of the treatment assignment mechanism from potential outcomes. The research design that best satisfies this condition is a randomized experiment, in which the treatment assignment is random. However, experiments are rarely possible in the social sciences, and most data come from observational studies. In this case, the treatment assignment mechanism is usually unknown and it is much harder to satisfy the condition of ignorability. If the treatment was selected on the basis of some factors that are correlated with the outcome and not accounted for in the model (selection on unobservables), then the estimates of causal effects will be biased.

These two approaches to causality in social science research (one that is based on the search for mechanisms vs. counterfactual statistical analysis) do not necessarily contradict each other, but can be complementary (see Morgan and Winship, 2007, pp.230-237). If one wants to understand how and why one phenomenon affects another phenomenon, the first step is to establish that the causal association between two variables, as defined by statistical criteria, truly exists. Once this association is established (or, at least, supported by the empirical evidence to the extent that is possible given the data and methods currently available), one can proceed to the analysis of the causal mechanisms that explain it. If the statistical association between two variables is merely spurious (or severely biased), then the search for causal mechanisms can be misleading.

Hence, in the empirical analysis where researchers aim to establish a causal effect of class on some outcome variable, the first task is to ensure the condition of ignorability. In the sociological literature the usual approach is to include class as a predictor variable in a regression equation where the outcome of interest is the dependent variable, along with other predictors (possible confounders) such as sex, age, education, income, location, etc. This approach is definitely useful for establishing the conditional association of class with the outcome variable of interest, but perhaps less useful when the task is to identify causal effects.

Summarizing the literature, Morgan and Winship (2007) provide several reasons why ordinary regression can produce biased estimates of causal effects. While their discussion is limited to the case of linear regression, similar arguments can be applied to all generalized linear models.

First, regression estimates may suffer from the omitted variable bias. If there is a pre-treatment variable that is correlated both with the treatment and the outcome and that is not observed and cannot be controlled for, then estimates of the treatment effect will be upwardly biased. This applies to class analysis that often fails to control for important factors that may affect membership in different classes. For instance, it is clear that intellectual abilities and psychological characteristics and attitudes may influence occupational choice and, hence, membership in occupational classes. IQ and psychological traits are also very likely to be correlated with many outcome variables. However, sociologists only rarely have data on IQ and psychological traits and these variables are not usually accounted for in the analysis. This creates the omitted variable bias of unknown size for the effects of class. Another problem is reverse causality that is a possibility of a causal effect of the outcome on the treatment. In econometrics the problems of omitted variable bias and reverse causality are known as endogeneity.

Second, the identification of the treatment effect in regression depends on the parametrization of control variables. Most researchers usually rely on the linearity assumption, modelling the linear association between independent and dependent variables. Even in the case of logit and other non-linear models, there is still the assumption that continuous independent variables are linearly associated with odds ratios or some other transformations of the original outcome variable. Surely, analysts can relax this assumption by adding quadratic, cubic or other non-linear terms, but even in this case modelled functions do not necessarily reflect the 'real' shape of the association between the variables. Besides, control variables can interact with each other, and a correctly parametrized model that intends to estimate causal effects must include not only flexible coding of control variables, but also all interactions between them (i.e., the model should be saturated or fully parametrized).

Third, even if there is no omitted variable bias and all control variables are measured and parametrized correctly, regression estimates can hide the heterogeneity of causal effects. For example, in the case of class the size of the effect of being a professional rather than an unskilled worker may depend on sex, age, education and many other variables. Morgan and Winship (2007) show that unless all the relevant interactions between the treatment variable and the control variables are included in the model, the treatment effect is estimated with the conditional-variance weighting scheme (in the case of an OLS regression) and is not the average treatment effect researchers are usually interested in.

Therefore, unbiased estimates of causal effects in regression-based class analysis depend on many assumptions that are usually hard, if not impossible, to satisfy even in the case of one treatment variable (see also Sobel, 1996, 2000; Freedman, 1999; Cox and Wermuth, 2001; Gangl, 2010). It becomes even harder when researchers aim to estimate the causal effects of several independent variables in the same regression equation and compare the size of coefficients. The results of these comparisons may be hard to interpret meaningfully.

Of course, this is not to say that all regression-based class analysis is useless. If a statistical association of class with some outcome variable is established (conditional on possible confounders), this may serve as an indication that class *may* have a causal effect on this outcome. Besides, as discussed in the next section, regression can be used as a useful descriptive tool. However, there is always a possibility that the effect is spurious. Biased estimates may be particularly misleading when the task is not just to answer a qualitative question of whether the causal effect of class is present or not, but to be more or less precise with the estimation of the size of the effect.

2.3.2 Class as a descriptive concept

If ordinary regression does not in most cases give unbiased estimates of causal effects, what is the solution to this problem? First, analysts can use other methods for estimating causal effects, developed by statisticians and econometricians. Many of these methods are based on regression. Among the most popular are regressions with instrumental variables that use random variation in the treatment assignment that results from natural experiments to avoid the omitted variables bias, fixed-effects regressions that use longitudinal data to account for time-constant unobserved traits, and propensity score matching that allows to balance treatment and control groups in respect to the treatment assignment mechanism. None of these methods provides a perfect solution to the problem of causal inference from observational data, but the estimates are less biased than in the case of ordinary regressions.

Another solution is simply to use regression as a descriptive tool. There is nothing in regression analysis that precludes results from being interpreted descriptively and not causally. The descriptive approach to regression analysis is deeply rooted in the sociological and statistical traditions, as is made clear in the following quotations.

> "Regression analysis is inherently a descriptive tool" (Berk, 2004, p.206).

> "In other words, one cannot use regression analysis to infer cause. We shall see later that the same conclusion holds for multiple regression and regression with more than one equation, those, too, are just ways to describe conditional distributions" (Berk, 2004, p.102).

> "Finally, and perhaps most important, many sociologists denigrate description and equate scientific explanation with causal explanation. From the point of view here, many sociological questions neither require nor benefit from the introduction of causal considerations, and the tendency to treat such questions as if they are causal only leads to confusion" (Sobel, 1996, p.376).

> "Least squares regression can be justified without reference to causality, as it can be considered nothing more than a method for obtaining a best-fitting descriptive model under entailed linearity constraints" (Morgan and Winship, 2007, p.123).

Abbott (1998) argues that sociologists should pay more attention to descriptive analytic techniques rather than try to infer causality from regression analysis, and as a descriptive technique regression is perhaps not the most useful.

> "... As a general method for understanding why society happens the way it does, much less as a strategy for simple description, causally interpreted regression is pretty much a waste of time. [...] Thus, we should not assume that science must be about causality. Much of real science is description. Sociology will not be taken seriously again as a general science of social life until it gets serious about description" (Abbott, 1998, p.174).

Goldthorpe (2001) whose perspective on causal analysis is by and large quite different from the one that is advocated in this chapter, agrees that regression can be justified as a merely descriptive tool.

> "What then may be suggested – as indeed the critics in question all in one way or another do – is that the whole statistical technology that has underpinned the sociological reception of the idea of causation as robust dependence, from Lazarsfeldian elaboration through to causal path analysis, should be radically reevaluated. That is to say, instead of being regarded as a means of inferring causation directly from data, its primary use should rather be seen as descriptive, involving the analysis of joint and conditional distributions in order to determine no more than pattern of association (or correlation). Or, at very most, representation of the data might serve to *suggest* causal accounts, which, however, will need always to be further developed theoretically and then tested as quite separate undertakings" (Goldthorpe, 2001, p.11).

The aim of descriptive analysis as applied to class can simply be to show class differentials in some chosen outcome variables. In some way, this is closer to the original idea of class analysis both in the Marxist and Weberian traditions. Neither Marx nor Weber were thinking of the effects of class "all other things being equal", but rather described how (and why) people in different classes have different life chances, interests or inclinations to collective action. The idea was that the structural position of people who formed the working class was different from that of those who formed the bourgeoisie, and this distinction led to class differences in economic, political and cultural outcomes and had important consequences for social life.

Technically, descriptive class analysis does not have to be bivariate. The aim of the analysis can be not simply to show, for instance, class differentials in mortality, but to stratify the association by other factors, such as sex, age, location, etc. The primary goal of the analysis after controlling for these variables in a regression equation would still remain descriptive and the results will not allow direct causal interpretations. But these descriptive models, even limited to the (broadly defined) regression framework, can be quite technically sophisticated and substantively rich, especially if more serious attention is paid to the functional form of the modelled associations and interactions between class and other predictors. Sometimes giving a clear descriptive account of the social phenomena of interest may be more useful than attempting to reach causal conclusions, especially when the data are ill-suited for this purpose. Moreover, accurately documenting statistical associations may suggest causal effects of class that can be further tested in a separate analysis.

The difference between descriptive and causal approaches to regression analysis is also important for selecting control variables. This is discussed in the next subsection.

2.3.3 Control variables in regression-based class analysis

Let us start with the rules for selecting control variables when the aim of regression analysis is causal. The idea of multivariate causal regression analysis with observational data is to control for the variables that determine selection for the "treatment".[1] That implies that control variables must precede the treatment in time. In other words, researchers should not control for the variables that could themselves be affected by the treatment.

When the aim of the analysis is to identify *causal* effects of class, income or earnings should not be controlled for. It is clear that occupational class directly affects earnings (and, as a consequence, income). When researchers want to estimate the causal effect of class on, for instance, mortality risks, controlling for earnings or income would in essence create an artefactual statistical world where all the classes are assumed to have equal earnings. This is clearly not the case; moreover, one of the most important mechanisms through which class can affect mortality risks is class-based earnings inequality. Directly controlling for earnings in this case would downwardly bias the true causal effect of class.

The same logic applies to all other cases of controlling for "post-treatment" variables in causal analysis with observational data. If class is the variable of causal interest, it is misleading to control not only for earnings or income, but

[1] By the "treatment" here and below I mean a causal variable of interest.

for all other "intermediate" variables that could be affected by class, even if the correlation between these variables and class is low. All post-treatment variables can in this case be regarded as "bad" controls.[2]

This problem has been recognized for some time in the statistical literature on causal analysis that does not recommend including post-treatment variables as controls in regression equations. Cox and Wermuth (2001) and Gelman and Hill (2007) provide an informal discussion of the problem, Rosenbaum (1984) gives a more formal treatment. See also Schisterman et al. (2009) for a discussion of the same problem in epidemiology (including a formal definition of the bias that results from overadjustment for post-treatment variables) and Wooldridge (2005) for an econometric discussion.

According to this logic, the often applied strategy of putting several variables (such as education, class, income, etc.) in a regression equation with the aim to establish which variable has a "stronger" effect on the outcome is only of limited value. Even if we brush aside the usual disadvantages of the causal regression analysis with observational data (omitted variable bias, possibility of reverse causality, etc.), including income, education and class as independent predictors in the same regression equation does not identify the separate causal effects of these variables. In fact, resulting coefficients are difficult to interpret meaningfully, at least as long as this interpretation is supposed to be causal.

Berk (2004) notes that if after including occupation in a regression equation education ceases to be statistically significant, this is by no means evidence of occupation having a "stronger" effect on the outcome variable than education, nor of education having no effect on the outcome at all. The same logic applies to occupational class and income. If income is associated with the outcome variable conditional on class and class is not associated with the outcome variable condi-

[2] When the "treatment" variable is education rather than class, it is equally misleading to control for occupation, class or other occupation-based measures, as long as the goal is to identify the causal effect of education. This is a mistake that econometrics textbooks often warn against (Angrist and Pischke, 2009, pp.64-68).

tional on income (at the conventional level of statistical significance), that does not mean that class has no association with the outcome at all.

First, as Berk (2004) remarks, this may indicate that the effect of class is "channeled" through income, i.e. class has the indirect effect on the outcome variable via income. Second, perhaps more importantly, the lack of statistical significance of regression coefficients does not prove the absence of the association. In other words, our inability to reject the null hypothesis does not prove that the null hypothesis is correct. The lack of statistical significance may result from many factors, including the insufficient power of the test as a consequence of the limited sample size or the inclusion of several highly correlated variables in the regression equation. Correlation between class, occupational status, education and income is usually quite strong and that increases the standard errors of the coefficients for these variables if they are added in regression simultaneously. As a consequence, null hypotheses of the absence of the association become harder to reject, even with relatively large samples.

Moreover, the issue of simultaneously measuring the direct and indirect (via a "mediator" variable) effects of the "treatment" variable in the regression framework requires caution. For example, let us imagine that a researcher wishes to identify the effect of occupational class on attitudes towards immigration. Let us assume that there is no omitted variable bias and the researcher controls for *all* the variables that determine membership in different classes and may be correlated with immigration attitudes (i.e., education, IQ, social background, etc.). In practice, this can never really be achieved, as some of these variables are unobservable, but we will make this assumption to further simplify the discussion. Let us then assume that the researcher wishes to decompose the effect of class into the direct effect on attitudes towards immigration and the indirect effect via income. The researcher runs a regression, in which he or she includes, apart from control variables, class and income and finds that the effect of class is close to zero after controlling for income (although without income the effect of class is significantly different from zero). Would this indicate that there is no direct effect of class on attitudes towards immigration, and all the effect is mediated via income?

Gelman and Hill (2007, p.190-194) show that this is not necessarily the case and may be true only after making further assumptions. They give a hypothetical example of a study of the effect of a child care intervention on children's IQ that controls for an intermediate variable, the quality of parenting. With their simulated data, regressing IQ on both variables (child care intervention and parenting quality) simultaneously produces false results for the treatment effect. They conclude:

> "Some researchers who perform these analyses [*based on the inclusion of intermediate variables – AB*] will claim that these models are still useful because, if the estimate of the coefficient on the treatment variable goes to zero after including the mediating variable, then we have learned that the entire effect of the treatment acts through the mediating variable. Similarly, if the treatment effect is cut in half, they might claim that half of the effect of the treatment acts through better parenting practices or, equivalently, that the effect of treatment net the effect of parenting is half the total value. This sort of conclusion is *not* generally appropriate, as we illustrate with a hypothetical example. [...]
>
> The regression controlling for the intermediate outcome thus implicitly compares unlike groups of people and underestimates the treatment effect, because the treatment group in this comparison is made up of lower-performing children, on average. A similar phenomenon occurs when we make comparisons across treatment groups among those who exhibit good parenting. [...] This estimate does not reflect the effect of the intervention net the effect of parenting. It does not estimate any causal effect. It is simply a mixture of some nonexperimental comparisons" (Gelman and Hill, 2007, p.191-192).

The reason for the inconsistency of these estimates is that the treatment may have a heterogeneous effect on the intermediate outcome. For instance, for some people being in the class of professionals may greatly increase their income. For others, however, this may not have the same effect. There may be some systematic unobserved differences between these groups of people. By simultaneously regressing the outcome variable on class and income, we implicitly compare the outcomes of classes within groups defined by income. These groups, however, may differ in terms of some important unobserved characteristics, correlated with the outcome. Even if the ignorability of the treatment has been achieved (via randomization or stratification by the treatment-assignment variables), we need to make sure of the ignorability of the intermediate variable to produce unbiased results. This requires a new set of assumptions.

Therefore, even when the aim of the analysis is to disentangle the direct and indirect effects of the treatment, controlling for "post-treatment variables" in regression can hardly be justified. For a more detailed discussion with examples see Rubin (2005).

These remarks, however, are relevant only for the cases when the aim of regression analysis is causal. Things become different when regression analysis is performed descriptively in order to establish statistical associations within groups defined by independent variables. The idea of "post-treatment" variables is not relevant for descriptive analysis, simply because there is no "treatment" and all independent variables in the regression equation have equal status.

Quite obviously, this does not mean that descriptive regression models should follow the "kitchen sink" rule and include all available variables that may be associated with the outcome. Independent variables should be selected so that comparisons within the groups defined by these variables are substantively meaningful and justified by the logic of the research questions. When regression coefficients from these models are given a substantive interpretation, it is important to remember that all coefficients need to be interpreted with other variables in the regression hold constant. Returning to the example with class, income and immigration attitudes, the coefficients on dummy variables for classes should be interpreted as a weighted average difference in immigration attitudes between classes *within groups formed by income*. Similarly, coefficients on income (if entered linearly) should be interpreted as a linearly constrained average association between income and immigration attitudes *within classes*, weighted with the size of the classes. Both sets of coefficients can be quite different from the *causal* effects of income and class on immigration attitudes.

The descriptive interpretation of regressions imposes certain restrictions on the number of independent variables that may be simultaneously included in a regression equation. If there are too many predictors, especially if they are strongly correlated, it may be hard to meaningfully interpret regression coefficients.[3]

2.3.4 Modelling strategy

Most of the statistical analysis that I present in the thesis is descriptive (with the possible exception of chapter 3 where I use fixed-effects regressions to produce results that can, under certain assumptions, be interpreted causally). It will become clear in the following chapters that this descriptive analysis is not limited to bivariate associations and involves multivariate modelling. The aim is to document Russian class inequalities in labour market outcomes and health, both crude and adjusted for a number of factors, and to compare Russia with Western countries.[4] This strategy dictates the choice of terminology. I generally avoid using terms like "to affect", "to influence" and other terms that imply causality when presenting the results of the analysis. Instead in most cases I discuss associations and relationships between the variables and the social phenomena that they measure.

[3]Christopher Achen, the former president of the Political Methodology section of the American Political Science Association, introduced "A Rule of Three" (ART) that states: "A statistical specification with more than three explanatory variables is meaningless" (Achen, 2002). Achen continues: "If one needs several more controls, then there is too much going on in the sample for reliable inference. No one statistical specification can cope with the religious diversity of the American people with respect to abortion attitudes, for example. We have all done estimations like these, underestimating American differences and damaging our inferences by throwing everyone into one specification and using dummy variables for race and denomination. It is easy, but it is useless, and we need to stop" (Achen, 2002, p.446). See also Schrodt (2010). While I do not follow the Achen's "rule of three" in this thesis, I try to make sure that the number of predictors is reasonable and the groups defined by them are meaningful.

[4]The last chapter of the thesis, in which I construct an occupational status scale for Russia, stands apart from this logic.

I also avoid including too many independent variables in regression equations, in particular in those cases when they can be closely correlated with class. For instance, simultaneously regressing the outcome variables on class and education, represented by two sets of dummy variables, may produce results that should be interpreted with caution. Regression coefficients on class in this case indicate average differences in the outcome between classes within the groups formed by education. In other words, we compare the outcomes for different classes first for people with a university degree, then for people with secondary education, etc. and then average the results, weighting by the size of educational groups.

There are several problems with this type of analysis. First, class and education are well correlated: there are only very few manual routine workers with a university degree, or professionals without a degree. Thus, making comparisons between classes within educational groups, we compare classes of a very different size, with the consequence that the results of these comparisons are less reliable.[5] Second, by averaging the differences between classes across educational groups we basically assume that the "effects" of class are roughly the same at each educational level. This may not be true. The latter assumption can be checked by adding to the model interactions between class and education, but when both variables are represented by a set of dummies, including interaction requires larger samples than those that are usually available. Including both class and education as predictors can still be a useful analytic strategy, but in some cases crude differentials between classes (perhaps adjusted for age, sex, location) would be more informative.

A similar argument applies to the simultaneous inclusion of class and income. The regression coefficient on income in this case would show average association between income and the outcome, estimated within the classes. That would be

[5]Moreover, relatively uneducated professionals and overeducated unskilled workers are most likely quite specific groups of people in terms of their unobserved characteristics. However, this becomes a problem only when the aim of the analysis is causal rather than descriptive.

interesting if the aim is to see if there is an association between income and the outcome, net of the occupational differences as defined by class. On the other hand, the coefficients on class would estimate average association between class and the outcome for people *with the same income*. In other words, that would be a comparison of, say, professionals and manual workers with the same level of income. Usually this is not the case, and these comparisons are only meaningful if they are guided by specific research questions.

2.4 Operationalization and coding of EGP class

As shown in section 2.2, the EGP class theory is based on the differentiation of the types of employment contracts. However, in most surveys researchers rarely have detailed data on the different aspects of respondents' employment contracts. Empirical operationalization of EGP class is derived from other variables such as employment status (employee or self-employed), supervisory status and occupation. Occupations, coded according to one of the detailed occupational schemes such as ISCO88, are assigned to EGP classes (taking into account employment and supervisory status) with special conversion tools.

Surprisingly, despite the popularity of the EGP class schema in the social stratification research community, there is no universally accepted conversion tool for coding EGP class from occupation, supervisory and employment status. There are at least three different tools that have been used in empirical research. The first tool originates from the CASMIN project and was used in the studies of social stratification in post-Soviet Russia conducted by Gerber and Hout (1998, 2004). It is not publicly available.[6] The second tool was designed by Ganzeboom and Treiman (1996, 2003) and is publicly available on the Internet[7] and in the package `isko` for Stata. Third, a group of researchers recently constructed a new occupa-

[6] I thank Ted Gerber for sending the conversion tool to me.

[7] `http://home.fsw.vu.nl/hbg.ganzeboom/isko88/index.htm`

tional class schema on the basis of the EGP schema. The British version of the schema is called the NS-SEC (the National Statistics Socio-Economic Classification) and is now the official class schema used by the Office for National Statistics (Rose et al., 2003). Its European analogue, designed for use in cross-national research, is the ESeC (European Socio-Economic Classification)(Rose et al., 2001; Rose and Harrison, 2007, 2010). While the theoretical basis of this schema remains the same as in the "old" EGP schema, the allocation of occupational groups to classes is in some cases different.

One issue that should be given special attention when coding class in Russia is the internal consistency of the salariat. Both EGP and ESeC separate higher and lower salariat, and both of these classes include managers and professionals. It is argued that while managers and professionals are clearly different according to a number of characteristics (for instance, social status (Chan and Goldthorpe, 2004)), these differences are not relevant to the theory of social class and, therefore, are not class related. Recently, Mills showed that in terms of the characteristics of their employment contracts, managers and professionals in Britain can hardly be separated (McGovern et al., 2007, ch.3).

On the other hand, Gerber and Hout (2004) demonstrate that in post-Soviet Russia the separation of managers and professionals improves the fit of intergenerational mobility models. While this cannot be taken as an evidence of the differences in employment contracts between managers and professionals, these results show that for many empirical applications the separation of these two groups is useful. It may be especially relevant in the context of the Russian transition to a market economy, in which many professionals were among the losers and some groups of managers employed in the private sector in finance, services and trade, were among the winners. To further investigate whether managers and professionals in Russia do differ in class-relevant characteristics, I follow Gerber and Hout (2004) and in all the analyses separate the classes of managers, higher professionals and lower professionals.

In this section I compare three different versions of coding EGP class (the ESeC, Ganzeboom-Treiman and Gerber-Hout versions) using the Russian data from RLMS 2006. The ESeC was coded with a Stata translation of the official syntax, available on `http://www.mzes.uni-mannheim.de/download/ESeC_full_version_for_ESS.do`. The Ganzeboom-Treiman version was coded with the Stata routine `iskoegp`, available in the package `isko`. The Gerber-Hout version was coded with a Stata routine sent to the author by Ted Gerber. The ESeC and Ganzeboom-Treiman conversion routines were modified to separate managers from professionals. All respondents with occupations from the ISCO-88 major group 1 ("Legislators, senior officials and managers") were coded as managers, as long as they were not self-employed.

Tables 2.1 and 2.2 present the cross-tabulations of ESeC classes and EGP classes coded with Ganzeboom-Treiman and Gerber-Hout conversion tools (based on the data from RLMS 2006). Although in general the schemes are consistent with each other, there are differences in coding some occupations.

Table 2.1 shows that some higher professionals in the Ganzeboom-Treiman (GT) version of the EGP schema are coded as lower professionals or even lower supervisors and technicians in the ESeC. These are people with occupations such as economists[8], physical and engineering science technicians, administrative secretaries, stock clerks, etc. In the GT-EGP schema many of them were promoted to higher professionals due to their supervisory status.

Some lower professionals in the GT-EGP were coded as higher professionals (computer programmers, teaching professionals nec[9], business professionals nec), intermediate workers (sales representatives, finance and sales associate professionals nec, decorators and commercial designers, etc.) or lower supervisors (safety,

[8]In Russia, "economists" are midlevel business professionals employed in many enterprises in industry and services rather than academic scholars or public servants.

[9]Not elsewhere classified.

Table 2.1: Comparison of the ESeC and the Ganzeboom-Treiman version of the EGP schema[a]

ESeC	Ganzeboom-Treiman (GT-EGP)											
	Ia/IIa. Managers	Ib.Higher professionals	IIb.Lower professionals	IIIab.Routine non-manual	IVa.Self-employed (with employees)	IVb. Self-employed (without employees)	V.Manual supervisors	VI.Skilled manual	VIIa.Semi-skilled manual	VIIb.Farm labour	IVc. Self-employed (farm)	n
1a/2a.Managers	271	0	0	0	0	0	0	0	0	0	0	271
1b.Higher professionals	0	534	140	0	0	0	0	0	0	0	0	674
2b.Lower professionals	0	236	774	99	0	1	0	0	0	0	0	1110
3.Intermediate	0	0	182	306	0	0	0	0	0	0	0	488
4.Self-employed	0	2	1	0	90	113	0	0	2	0	2	210
5.Self-employed (agriculture))	0	0	0	0	0	0	0	0	0	0	7	7
6.Lower supervisors and technicians	0	32	151	0	0	0	128	9	89	5	0	420
7.Lower sales and services	0	0	0	595	0	0	0	70	78	0	0	743
8.Lower technical	0	0	0	0	0	0	0	699	99	19	0	817
9.Routine	0	0	0	5	0	0	0	364	1252	93	0	1714
n	271	804	1248	1005	90	114	128	1142	1520	117	15	6454

[a] Data source: RLMS 2006.

Table 2.2: Comparison of the ESeC and the Gerber-Hout version of the EGP schema[a]

	Gerber-Hout (GH-EGP)										
ESeC	Ia/IIa. Managers	Ib.Higher professionals	IIb.Lower professionals	IIIa.Routine non-manual (higher)	IIIb.Routine non-manual (lower)	IVab.Self-employed	IVc. Self-employed (farm)	V.Manual supervisors	VI.Skilled manual	VIIa.Semi-skilled manual	VIIb.Farm labour	n
1a/2a.Managers	269	0	1	0	0	1	0	0	0	0	0	270
1b.Higher professionals	0	295	378	1	0	0	1	0	0	0	0	675
2b.Lower professionals	0	136	640	361	3	2	0	0	0	0	0	1142
3.Intermediate	0	0	33	471	0	0	0	0	0	0	0	504
4.Self-employed	0	0	0	0	0	245	7	0	0	0	0	252
5.Self-employed (agriculture))	0	0	0	0	0	3	4	0	0	0	0	7
6.Lower supervisors and technicians	0	0	7	133	69	0	0	193	9	31	4	446
7.Lower sales and services	0	0	0	124	599	0	0	0	20	0	0	743
8.Lower technical	0	0	0	0	0	0	0	0	749	87	19	855
9.Routine	0	0	0	28	34	0	0	0	214	1512	93	1881
n	269	431	1059	1118	705	251	12	193	992	1630	116	6776

[a] Data source: RLMS 2006.

health and quality inspectors, stock clerks, salespersons with supervisory functions) in the ESeC.

Routine non-manual workers in the GT-EGP were mostly coded to intermediate and lower sales and services classes in the ESeC, but some were assigned to lower professionals (nursing and midwifery associate professionals).

Some skilled manual workers in the GT-EGP were coded as unskilled routine workers (cooks, earth-moving plant operators, crane and hoist operators, steam-engine and boiler operators, etc.) and lower sales and services workers (fire-fighters, police officers, hairdressers) in the ESeC.

Most unskilled workers in the GT-EGP were coded in the same way in the ESeC, but some were promoted to skilled workers (bricklayers, concrete plasterers and finishers, glaziers, railway brakers and signallers) or coded to the lower sales and service class (institution-based personal care workers, prison guards).

In general, the two schemes are quite similar, but the ESeC has a smaller salariat (this is consistent with Evans and Mills (2000)) and a larger class of routine non-skilled workers if compared to the GT-EGP.

Table 2.2 compares the ESeC with the Gerber-Hout (GH) version of EGP class. The GH-EGP has an even smaller salariat than the ESeC, and a particularly small class of higher professionals (mostly because of the demotion of engineers to lower professionals). The GH-EGP also has a larger routine non-manual class and codes more manual workers as skilled rather than unskilled.

The attribution of occupations to particular classes, based on expert assessment, is by definition subjective. It is hard to say, at least without a detailed analysis of employment contracts at the occupational level, which way to code EGP class is more "correct". Perhaps consistency in applying the same class schema is more important.[10] In all the subsequent analyses in the thesis I use the ESeC. This is a new schema that was created to serve as a tool of cross-national

[10]It is unfortunate that the results of statistical class analysis are often reported without mentioning which conversion tool was used to code class.

Table 2.3: Most typical occupations in ESeC classes[a]

ESeC	Men	Women
1a/2a.Managers	General managers nec; other department managers nec; production and operations department managers in manufacturing	General managers nec; other department managers nec; general managers in the wholesale and retail trade
1b.Higher professionals	Architechts and engineers nec; architects, town and traffic planners; other teaching professionals nec; electronics and telecommunications engineers; medical doctors	Other teaching professionals nec; accountants; medical doctors; architects and engineers nec; business professionals nec
2b.Lower professionals	Military officers; police inspectors and detectives; civil engineering technicians; physical and engineering science technicians nec; mechanical engineering technicians	Nursing associate professionals; secondary education teaching professionals; economists; pre-primary education teaching professionals; bookkeepers; primary education teaching professionals
3. Intermediate	Sales representatives; military officers; athletes and sports persons	Bookkeepers; pre-primary education teaching associate professionals; sales representatives; secretaries
4/5.Self-employed	General managers in wholesale and retail trade; general managers nec; shop salespersons; building finishers	Shop salespersons; general managers in wholesale and retail trade
6.Lower supervisors and technicians	Building caretakers; safety, health and quality inspectors; stock clerks	Safety, health and quality inspectors; shop salespersons; stock clerks; cooks
7.Lower sales and services	Police officers; shop salespersons; stock clerks	Shop salespersons; institution-based personal care workers; cashiers and ticket clerks; stock clerks; transport clerks
8. Lower technical	Building electricians; mechanics and fitters; plumbers and pipe fitters; carpenters and jointers; building finishers; railway brakers, signallers and shunters	Bakers, pastry-cooks and confectionary makers, plasterers; painters
9.Routine	Heavy truck and lorry drivers; building caretakers; motor-vehicle drivers nec; freight handlers; car, taxi and van drivers; earth-moving plant operators	Helpers and cleaners in offices and hotels; cooks; building caretakers; doorkeepers and watchpersons; hand packers; farm-hands and labourers; steam engine and boiler operators; waitresses and bartenders

[a] Data source: RLMS 2006. Occupations are ordered starting from the most typical. “nec” is “not elsewhere classified”.

analysis and was validated with the data from several countries (Rose and Harrison, 2010).[11] It has a clear and publicly available syntax. Also, in cases where the ESeC and the GT-EGP are in disagreement, the ESeC seems to have better face validity, at least for Russia.

Table 2.3 shows the most typical occupations in each ESeC class, separately for men and women. As there are only very few people in the self-employed agricultural class (class 5), they are combined with the rest of the self-employed (class 4). Occupations in each class are ordered according to the number of people in them, starting from the most popular. Some occupations are in several different classes at the same time, as the ESeC takes into account not only occupation, but also supervisory and employment status.

The table shows that there are substantial gender differences in the occupational structure of classes. In chapter 3 I present and discuss more detailed descriptive statistics for the dynamics of the class structure in post-Soviet Russia for men and women.

To code class, the ESeC requires data on occupation and employment and supervisory status (unless a simplified version of the conversion is used that requires only occupation). Thus, class can be assigned only to people who are currently employed. To code class for the unemployed and people who are not in the labour force (for example, retired), information on their last occupation can be used. For most of the analyses in this thesis that look at the class differences in employment contracts and earnings, this is not a major problem as the unemployed and people outside the labour force can be excluded from these analyses. However, in chapter 5 that deals with the class differences in mortality, I use retrospective data on occupation in 1990 and 1985 to code class when information on current occupation is not available.

Another issue is coding class for women. There are two main approaches to

[11] Also see validation reports published on `http://www.iser.essex.ac.uk/research/esec`.

this. First, class can be coded with a woman's own occupation. However, this makes it difficult to code class for housewives and other women outside of the labour force. The second approach is to code class for women according to the highest class in the household, i.e. often assigning them the class of their husbands. As in the case of the unemployed, in most of the analyses in this thesis the choice between these two approaches is clear. In the study of the employment contracts and age variation in earnings class should be coded according to individual rather than household characteristics, as the theory of class relates individual class and employment characteristics. Moreover, the discussion about which of the two approaches is more suitable is more relevant for the UK than for Russia. In Russia women's labour force participation rate has traditionally been quite high. In the RLMS for 2006, ESeC class could be coded for 80% of men and 76% of women aged 23 to 55 (using information only on current occupation). As the difference between labour force participation rates for men and women in Russia is low and coding women's class with their own occupation does not lead to major selection bias, I use individual class for women in the study of the class differentials in mortality.

2.5 Summary

In this chapter I introduce and discuss the concept of social class as it is usually understood in contemporary quantitative sociology. Then I review the theoretical foundations of the EGP class schema that is used in further statistical analysis in the thesis. The central part of the chapter discusses the difference between descriptive and causal approaches to the class analysis in quantitative sociology. I argue that given the difficulties of causal analysis with observational data, descriptive analysis is often more useful. Finally, I describe the differences between three operationalizations of EGP class and present arguments in favour of one of them, the European Socio-Economic Classification (ESeC). In the next chapter, I discuss the dynamics of the class structure in post-Soviet Russia and analyze the differences between classes in terms of employment contracts and unemployment risks.

Chapter 3

Occupational Class, Employment Contracts and Economic Security in the Russian Labour Market

The main goal of this chapter is to check the construct validity of the ESeC schema in Russia. I explore class differences in employment contracts, fringe benefits and unemployment risks. Using panel data, I provide both a descriptive account of class differentials in these economic outcomes and fixed-effects estimates of the effects of class. I also discuss the dynamics of the class structure in post-Soviet Russia.

3.1 Validation of the EGP and ESeC class schemes

Operationalization of EGP class 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 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 context.

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 described in chapter 2. 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.

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 corresponded 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 runs within class 2 (lower managers and professionals), suggesting a smaller salariat compared to the usual operationalization of the EGP class.[1]

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.

[1] Note that, as discussed in the previous chapter, the ESeC has a smaller salariat compared to the EGP schema.

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 the ESeC is correlated with the measures of job autonomy, career prospects and the indicators of piece-wise and time-related compensation. There are also differences across the ESeC classes in the risks of poverty and deprivation, unemployment risks, the 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 (see a discussion in 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.

3.2 Validation strategy

The validation strategy that I apply in this chapter 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 to estimate the effects of class net of time-constant unobserved factors. 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 the 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 3.6).

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.

3.3 Data and measures

The data come from the pooled RLMS sample for the years 1994 to 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:

- *Sex.*

The analysis was conducted jointly for men and women, with a control for sex. Therefore, class effects represent weighted average 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) stressed 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.

3.4 Modelling strategy

The statistical models presented in this chapter 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 time-constant 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 the 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 the 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).

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

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 chapter, 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 cases, I estimate standard errors with the robust variance matrix, adjusted for the correlation of residuals for the same individuals, as programmed in the Stata's option `cluster` (Wooldridge, 2003).

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

The logic of the models presented so far is descriptive. I analyze if 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 high correlation between class and education and the difficulties with the interpretation of the results of this model (see chapter 2 for details). 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.

$$y_{ij} = \alpha + \gamma_j + \beta_{ij} + \epsilon_{ij}, \tag{3.1}$$

where γ_j are the 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 people in our sample experienced both formal and informal employment at different points of time. 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. The fixed-effects estimation for this variable does not produce meaningful results and I do not present it in this chapter.

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 3.1 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 for continuous variables (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 3.7.

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.

3.5 The class structure in post-Soviet Russia

Table 3.1 shows the dynamics of the class structure in Russia from 1994 to 2006, separately for men and women. The same information is graphically displayed in Figures 3.1 and 3.2.

Several conclusions can be made. Compared with Western European countries, there is a higher proportion of manual workers, especially among men. In 2006,

Table 3.1: 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.

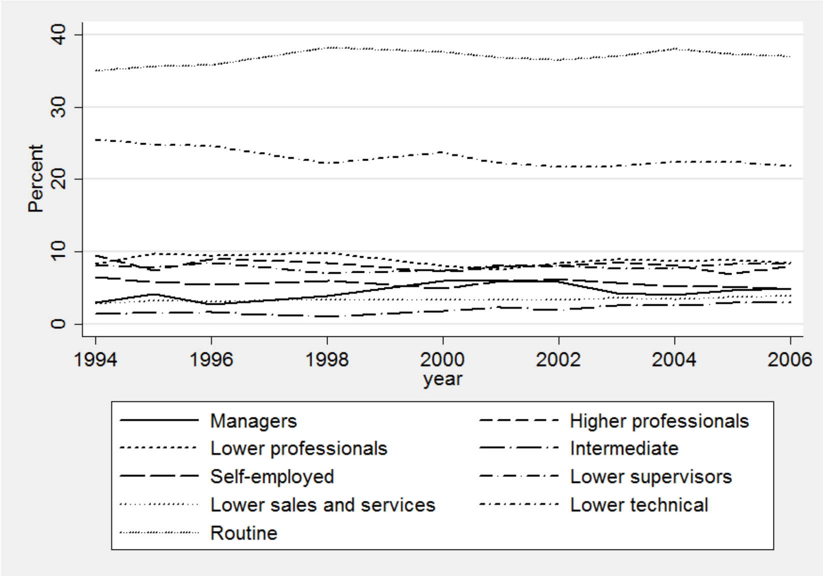


Figure 3.1: The class structure in Russia, men, 1994-2006. The data for 1997 and 1999 are missing.

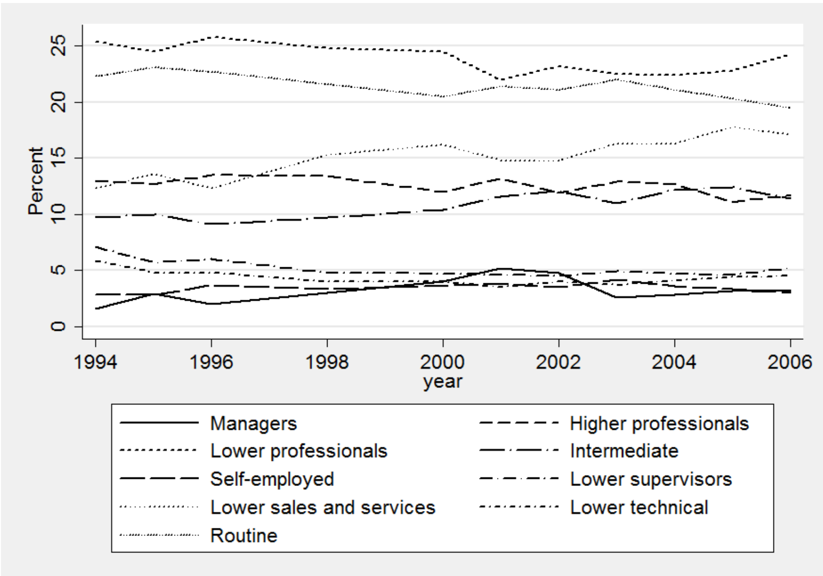


Figure 3.2: The class structure in Russia, women, 1994-2006. The data for 1997 and 1999 are missing.

37% of employed Russian men were routine (non-skilled) manual workers, and 22% were lower technical (skilled) manual workers. There were relatively few managers, the self-employed and professionals. (The comparison with Western European 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 occupations as nursing and secondary school teaching). The next classes by their size are routine workers and lower sales and service 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 the 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 very large and the distribution of the labour force across the classes remained relatively stable. The longer time-series for the class structure that began 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 and actually started in the Soviet period.

3.6 Class and informal employment contracts

Informal employment contracts became more widespread in Russia in the 2000s, although formally they are a violation of the 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 3.3 shows the change in the percentage of workers who had informal employment contracts from 1998 to 2006.[2] In 1998 only 2% of people employed in organizations had informal contracts. By 2006 this percent rose to 7%.

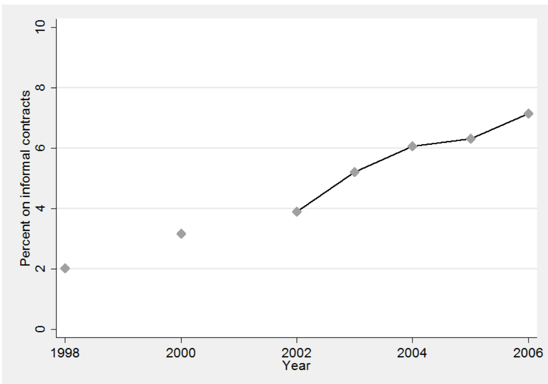


Figure 3.3: Percent of informally employed, 1998-2006. The data for 1999 and 2001 are missing.

Figure 3.4 shows the distribution of informal contracts across the ESeC classes

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

in the pooled RLMS sample for 1998-2006. The labour contract classes (lower sales and service, lower technical and routine) have the highest percentage 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.

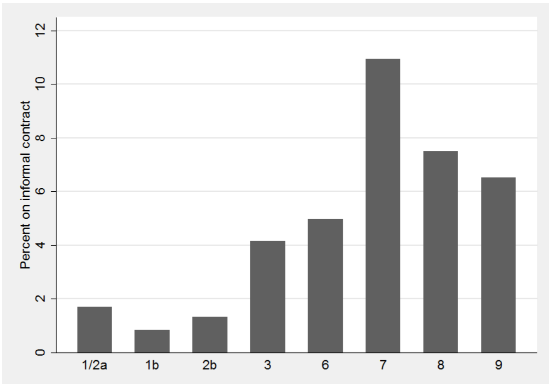


Figure 3.4: Distribution of informally employed across ESeC classes, 1998-2006. 1/2a - managers, 1b - higher professionals, 2b - lower professionals, 3 - intermediate, 6 - lower supervisors and technicians, 7 - lower sales and service, 8 - lower technical, 9 - routine.

Table 3.2 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 3.4.

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 the sector). The same applies 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 the 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 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 explain all the class differences in employment contracts.[3] 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 3.2, class effects in the fixed-effects model are consistent with the random-effects models. However, the differences in the coefficients between the

[3]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 statistically significant at the conventional level.

Table 3.2: 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 if informal. (1)-(4) are logit models with random effects, (5) is a conditional logit model (equivalent to "fixed effects"). The dummy variables for years are included in all models, but not shown. The analytic sample includes years 1998, 2000, and 2002 to 2006. Branch of the economy is only available in years 2004 to 2006; the year of the foundation of the firm in years 1998, 2000 and 2002. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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.

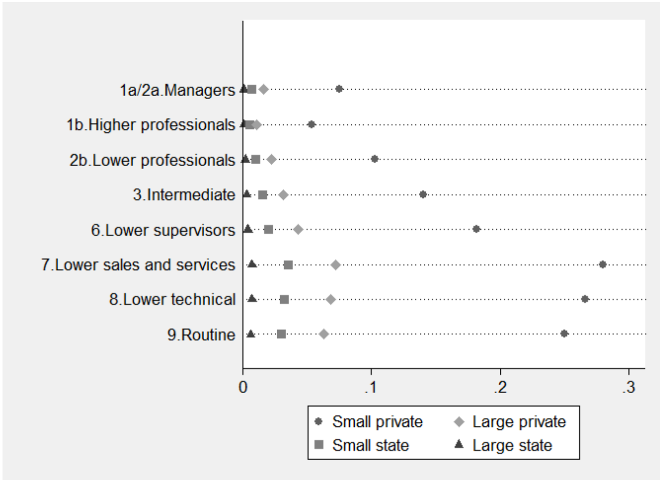


Figure 3.5: Probabilities of informal employment calculated from the population-averaged model with the same predictors as in model (2) in table 3.2. Other variables set at the following values: man, 40 years old, living in a city, year 2006.

The logit coefficients presented in Table 3.2 do not give a direct indication of class-specific probabilities of informal employment. Predicted probabilities, computed for model 2, are presented in Figure 3.5.[4] The figure shows class-specific probabilities of informal employment for large and small firms in the 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

[4]To predict probabilities of the outcome reported in figures 3.5 and 3.12 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 (2008).

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 3.7 and 3.8 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 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)[5], but with the outcome variable that identifies the voluntary or involuntary character of informal employment. The results are shown in Table 3.3.

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

[5]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 3.3 I use logit models with clustered standard errors instead of random-effects logit models. Individuals are treated as clusters.

Table 3.3: 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

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.

3.7 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 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, facilities for children 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 3.3. 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.

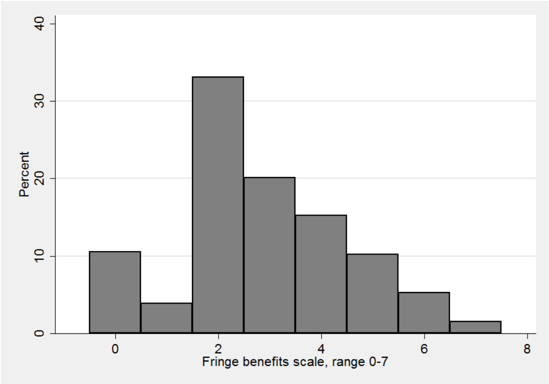


Figure 3.6: Distribution of the seven-item scale of fringe benefits

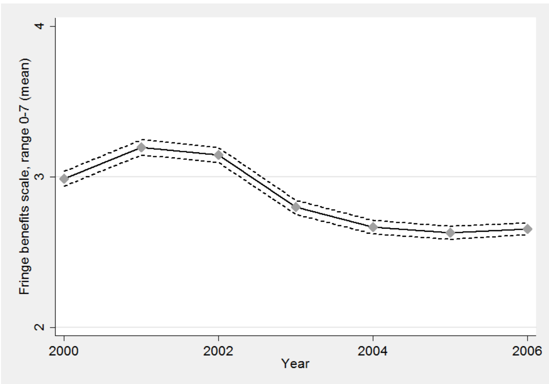


Figure 3.7: Mean fringe benefits index, 2000-2006. Dashed lines show 95% confidence intervals around the mean.

Figure 3.6 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.

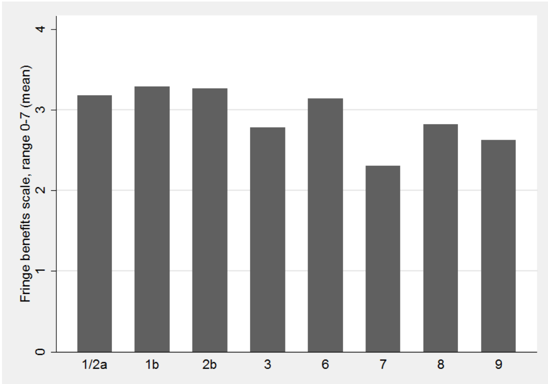


Figure 3.8: Mean fringe benefits index across the ESeC classes, 2000 to 2006. 1/2a - managers, 1b - higher professionals, 2b - lower professionals, 3 - intermediate, 6 - lower supervisors and technicians, 7 - lower sales and service, 8 - lower technical, 9 - routine.

Figure 3.7 is a time series plot of the mean of the fringe benefits scale in years 2000 to 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 3.8 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 3.4 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.

Table 3.4: 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 analytic sample includes years 2000 to 2006. The branch of the economy is only available in years 2004 to 2006, the year of the foundation of the firm in years 2000 to 2002. The data on informal contracts are unavailable for year 2001. *** p<0.01, ** p<0.05, * p<0.1

Model 2 adds control variables: sex, age, the 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.

Figure 3.9: Predicted mean values on the seven-item fringe benefits scale, by class and the economic sector. Calculated from model (2) + interaction effects between class and firm size and class and the economic sector. Other variables set at the following values: man, 40 years old, living in a city, year 2006.

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 3.4, but also includes the interaction effects between class and the size of the enterprise[6] and class and the sector of the economy (state

[6]To reduce the number of interaction terms, I combine small enterprises and enterprises with

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 the sector, and present the results in Figure 3.9. 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.

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.

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.

an unknown size and after that compare large and small enterprises.

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 3.4 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.

3.8 Class and unemployment risks

The last outcome variable I consider in this chapter 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.

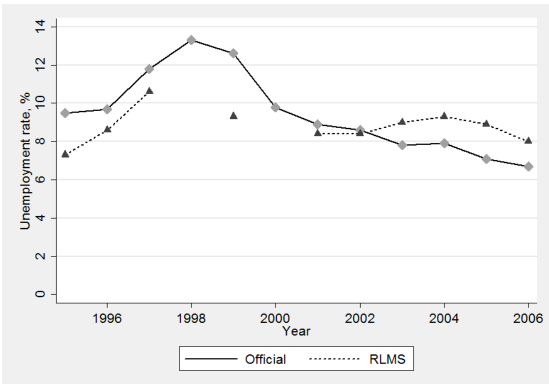


Figure 3.10: Unemployment rates in Russia, people aged 15-72. The solid line represents the official estimates of the Russian Statistical Office. The dashed line represents the estimates based on the RLMS.

Table 3.5: Regression models for unemployment risks[a]

variables	(1) coef	(1) se	(2) coef	(2) se	(3) coef	(3) se	(4) coef	(4) 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 RLMS round. The full sample includes years 1994 to 2005. The dummy variables for years are included in all models, but not shown. The branch of the economy is only available in years 2004 to 2006, the year of the foundation of the firm in years 1995 to 2002. ***p<0.01, ** p<0.05, * p<0.1

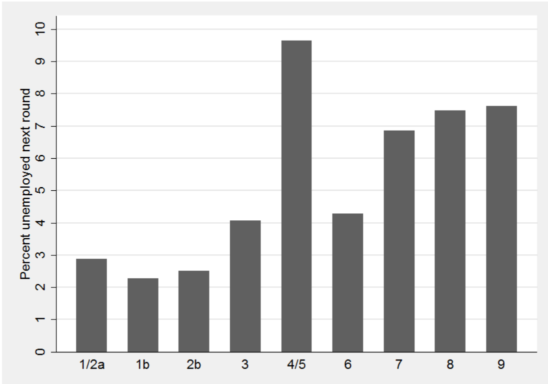


Figure 3.11: Percent of unemployed in the next RLMS round across ESeC classes, 1994-2005. 1/2a - managers, 1b - higher professionals, 2b - lower professionals, 3 - intermediate, 4/5 - self-employed, 6 - lower supervisors and technicians, 7 - lower sales and services, 8 - lower technical, 9 - routine.

Figure 3.10 compares the dynamics of the official unemployment rate calculated by the Russian Statistical Office (Rosstat, 1999-2009b), 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 to the 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 3.11 shows unemployment rates across the ESeC classes in the pooled RLMS sample. Unemployment rates were calculated as the percent of people in respective ESeC 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, 2001a).

Table 3.5 presents the regressions models with the same variables as in two previous sections.[7] 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.

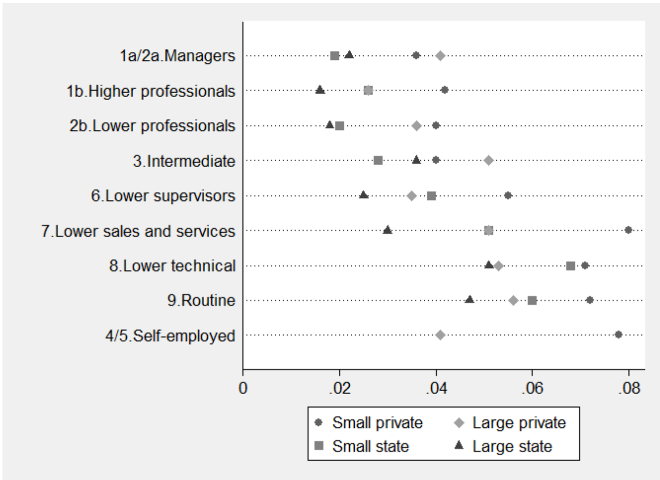


Figure 3.12: Probabilities of becoming unemployed in the next RLMS round, calculated from the population-averaged model with the same predictors as in model (2) in table 3.5 + interactions between class and firm size and class and the sector of the economy. Other variables set at the following values: man, 40 years old, living in a city, year 2000.

Figure 3.12 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

[7]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.

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 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

Table 3.6: Predicted outcomes for the models with the interaction between class and sex[a]

	probability of informal contract		mean fringe benefits		probability of unemployment next year	
ESeC class	men	women	men	women	men	women
1a/2a.Managers	0.03	0.01	3.0	3.1	0.04	0.03
1b.Higher professionals	0.02	0.01	3.2	3.2	0.03	0.02
2b.Lower professionals	0.04	0.01	3.0	3.1	0.04	0.02
3.Intermediate	0.08	0.04	2.6	2.8	0.07	0.04
4/5.Self-employed	NA	NA	NA	NA	0.12	0.07
6.Lower supervisors	0.07	0.04	3.0	2.8	0.04	0.05
7.Lower sales and service	*0.07*	*0.13*	*2.8*	*2.1*	0.07	0.07
8.Lower technical	0.08	0.09	2.7	2.7	0.09	0.05
9.Routine	0.08	0.07	2.5	2.6	0.09	0.06

[a] All predicted outcomes calculated from the models that include class, sex and the interactions between them as predictors. For binary outcomes, population-averaged logit models were used.

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.

3.9 Testing the interactions between class, sex and period

In all previous models I conducted the analysis jointly for men and women, averaging class differences in outcome variables for both sexes. Are class differences in economic security in Russia gender-specific? To test this, I fit models for three outcome variables with sex, class and interactions between them. The predicted outcomes are presented in table 3.6.

As already shown in table 3.2, on average men have higher risks of informal employment than women. When we introduce the interaction term between class and sex into the model, this pattern holds for all classes, except lower sales and service workers and, to a lesser extent, lower technical workers. Mean fringe benefits of men and women do not differ at statistically significant level. However, among lower sales and service workers men have a significantly higher index of fringe benefits than women. The probability of unemployment is higher for men than for women for all classes, except lower supervisors and technicians and lower sales and service workers.

Overall, the patterns of class inequality in economic security are similar for men and women. The exception is lower sales and service workers. Female members of this class have much lower economic security than their male colleagues and women in other classes. Perhaps this is not surprising, given that male and female lower sales and service workers largely represent different occupations. The most typical occupation for male lower sales and service workers is police officers (see table 2.3), employed in the public sector with a higher level of economic security. For women the most typical occupation is shop salespersons. This emphasizes that at least for some classes the analysis at the disaggregated occupational level can be beneficial.

I also tested the interaction between class and time in order to check if the class gap in economic security changes over time. To do this, I compared the gap between manual and non-manual classes in two periods, before and after 2001. The difference in the class gap in these two periods was not statistically significant for any of the three outcome variables.

3.10 Discussion

In this chapter 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 the

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 chapter. 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.

In this chapter I have presented only the evidence on class differences in the field of economic security. However, this is just one aspect of Goldthorpe's class theory. The next chapters present further evidence.

Chapter 4

Occupational Class, Age Segregation in the Labour Market and Age-Earnings Profiles in Russia

In this chapter I construct cross-sectional and longitudinal age-earnings profiles for Russia and explore possible reasons for their unusual shape. I also construct class-specific age-earnings profiles, show the heterogeneity in the shape of the profiles across classes and discuss this in light of Goldthorpe's class theory.

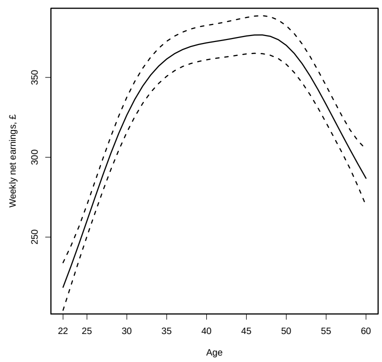
First, in section 4.1, I present the puzzle: the age-earnings profiles for Russian men have a different shape compared to the profiles for Great Britain and the USA. Then, in section 4.2, I discuss the approaches to the explanation of age-earnings profiles, developed in labour economics. Section 4.3 discusses other factors that can affect the shape of profiles. Section 4.4 describes data and methods. Next, in sections 4.5 and 4.6 I present and discuss cross-sectional and longitudinal profiles for Russian men and women for the period from 1991 to 2006. Section 4.7 introduces evidence of the effect of age segregation in the Russian labour market on the shape of profiles. Section 4.8 presents class-specific age-earnings profiles and discusses them in light of Goldthorpe's class theory. Section 4.9 provides some cross-national evidence on the shape of age-earnings profiles. Section 4.10 concludes.

4.1 Age-earnings profiles in Russia, the UK and the USA

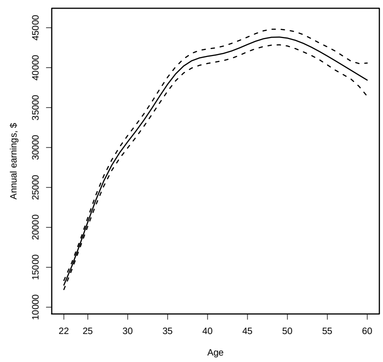
Figures 4.1(a) and 4.1(b) show the cross-sectional age-earnings profiles for men in Great Britain and the USA in 2006. The profiles follow the pattern, previously well documented in the literature. Men in their fourties have the highest average earnings. The earnings of older men are somewhat lower, while the youngest workers have the lowest earnings.

The age-earnings profile for Russia in 2006 looks strikingly different to those of Britain and the USA (see Figure 4.1(c)). Men's average earnings are at their highest at age 30 to 35. The earnings of older men are significantly lower. For instance, the average earnings of men aged over 50 are smaller than the average earnings of men at age 22, at the very beginning of their careers. This shape of the age-earnings profile for men in Russia has been documented before (Gerber and Hout, 1998; Brainerd, 1998; Gimpelson and Kapeliushnikov, 2007; Gorodnichenko et al., 2010), but it has never been properly examined and explained.

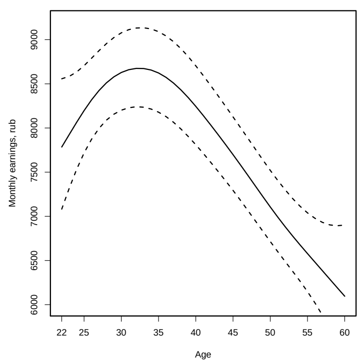
The explanations of the association between age and earnings have so far been developed mainly in labour economics, with very few sociologists working in this field. The dynamics of earnings over the life cycle is usually explained within the human capital paradigm, or, alternatively, by the theory of delayed payment contracts. In this paper I argue that there are other factors that can affect the shape of the age-earnings profiles that are particularly relevant to the Russian case. Age segregation in the labour market and the differences in the shapes



(a) Great Britain, LFS 2006, n=5656



(b) The USA, CPS March 2006, n=46546



(c) Russia, RLMS 2006, n=2525

Figure 4.1: Age-earnings profiles, Great Britain, the USA and Russia, men aged 22 to 60, nonparametric spline scatter plot smooths with the 95% confidence bands (dashed lines)

of age-earnings profiles across occupational classes are among these factors. The analysis of the data demonstrates that these two factors can help explain the shape of the age-earnings profiles in post-Soviet Russia, and in particular the differences between men and women.

4.2 Theories of the dynamics of earnings over the life cycle

There are a number of economic theories that explain the dynamics of men's earnings over the life cycle. The most well known among them is the human capital model, developed by Ben-Porath (1967). It suggests that earnings depend on the amount of human capital accumulated by individuals. People have more of an incentive to invest in human capital (i.e., education and skills) in the early stage of their lives in order to have more time to enjoy returns to the accumulated capital. As time passes, the investments in human capital diminish, until at some point in their lives people finally stop investing. Therefore, earnings rapidly increase while at a young age, keep increasing with a slower pace, reach a plateau and finally decrease due to the depreciation of human capital.

The Mincer earnings equation (Mincer, 1974; Willis, 1986; Weiss, 1986) is based on this theoretical model. Mincer suggested regressing earnings on education, age and age squared, and usually the model also includes a number of controls. [1] The main goal of the model is to estimate the returns to education. The dependence of earnings on age is modelled to be quadratic to account for the nonlinearity of the age-earnings association.

The human capital theory suggests a simple and elegant explanation of observed age-earnings profiles. However, several studies have shown that actual age-earnings profiles in many cases diverge from the pattern predicted by the theory.

[1] Age here is a proxy for work experience.

First, it was established that the quadratic function does not provide a perfect fit for the actual age-earnings relationship, as it understates the early career earnings growth and overstates the mid-career growth (Murphy and Welch, 1990; Robinson, 2003). Second, the decline of earnings at a later age that is observed in cross-sections, often disappears in longitudinal age-earnings profiles, most likely due to period effects: inflation and the growth of wages over time (Thornton et al., 1997; Johnson and Neumark, 1996; Myck, 2007).

Apart from the human capital model, there are other theories that try to explain the association between earnings and age. Employers may use earnings as a mechanism for solving the principal-agent problem in their relationships with employees. Workers' productivity is often difficult to monitor, and in order to solve the problem of shirking and malfeasance employers may use delayed payment contracts (Lazear, 1981; Hutchens, 1989). Young employees are paid less than their older colleagues even if their productivity does not differ. As workers grow older, their earnings increase. This creates an incentive for younger workers to work harder and stay longer with the same firm to receive an age premium in earnings that disappears if they move to another firm.[2]

Both the human capital and incentive pay theories predict that men's earnings increase as people get older and more experienced. As far as age-earnings profiles are concerned, the two theories do not contradict each other. Both human capital accumulation and incentive payment can affect the shape of age-earnings profiles.

Another theory that should be considered when explaining the shape of age-earnings profiles deals with demographic factors (Welch, 1979; Freeman, 1979). Some birth cohorts are larger than others and, therefore, the supply of workers in different birth cohorts varies. If we assume that the workers of a different age are imperfect substitutes in the labour market, then the wages of workers in smaller cohorts should be higher than the wages of workers in larger cohorts.

[2] Goldthorpe (2000) uses a similar argument as a theoretical foundation for the EGP class schema. It is discussed in more detail in chapter 2.

Most of the literature on age-earnings profiles deals with men's earnings only. Women frequently have intermittent careers and, therefore, their age and work experience are not so well correlated. This makes the human capital models for the age-earnings association for women more complicated. Some studies show that the size of birth cohorts affects earnings only for men, but not for women, perhaps because younger and older women are better substitutes in the labour market due to the breaks in women's careers (Freeman, 1979).

4.3 What factors can affect the shape of age-earnings profiles in Russia?

The economic theories outlined above suggest possible exaplanations for the unusual shape of cross-sectional age-earnings profiles for Russian men.

First I discuss possible implications of the human capital theory that suggests that the higher earnings of older men can be explained by the differences in accumulated human capital across the age groups. As described in more detail in the Introduction, in the 1990s Russia underwent the transition from a state economy to a market-based economy. Perhaps the human capital of older generations acquired in the Soviet period had little relevance for the new market economy. Younger people who were educated and acquired their work experience in the post-Soviet period, can have higher returns to human capital. Most economic research on this topic advocates this theory, however, without directly testing it (Brainerd, 1998; Gimpelson and Kapeliushnikov, 2007). In section 4.10 I discuss whether this theory holds against the evidence presented in this chapter.

The theory of delayed payment contracts suggests that the higher earnings of older men can result from the design of employment contracts that provide incentives for younger workers to stay in the same firm. As discussed in the Introduction, job mobility in post-Soviet Russia was high. It could be possible that due to high job mobility the earnings of Russian workers do not increase over the life cycle as workers do not receive the premium related to the firm-specific job experience. However, this hypothesis contradicts the evidence obtained in the studies conducted by labour economists (Sabirianova, 2002; Maltseva and Roschin, 2006). High job mobility in post-Soviet Russia was caused by low returns to the firm-specific work experience. In fact, employees benefited from changing jobs frequently. Those who stayed in the same job for a long time on average earned less than those who were mobile in the labour market.

The unequal size of birth cohorts can be another factor that affects age-earnings profiles. Birth cohorts in Russia are indeed different in size, mostly because of the effects of WWII. The cohort born in 1941-45 is small in size, and there is also a dip in the number of births in the late 1960s and early 1970s (children of the small cohort of the 1940s). On the other hand, the cohort born in the 1980s is relatively numerous.

However, the effect of the cohort size on age-earnings profiles was found to be small in most studies and it cannot by itself explain the large difference between the Russian profiles and the profiles in Britain and the USA. Besides, if there is an effect, it should work in the opposite direction, as smaller older cohorts should have some advantage in earnings and larger younger cohorts should be disadvantaged. The effect of the cohort size on earnings in Russia requires a separate study, but it is very unlikely that it can account for the observed shape of age-earnings profiles.

There are also other factors that can affect the shape of age-earnings profiles and that are often not taken into account in the economic literature. These are the effect of health on earnings, age segregation in the labour market and the effect of class composition.

It is well known that health affects earnings (Cutler et al., 2006). People with bad health have lower earnings than healthy people, other things being equal. In some sense, health can be considered a part of human capital that affects the productivity of workers. Compared with Western Europe and the USA, the health of older men in Russia is worse and, potentially, this can explain their lower earnings.

Another factor that can affect the shape of age-earnings profiles is age-based occupational segregation. Social scientists mostly paid attention to occupational sex segregation and its effect on the differences in earnings between men and women. The fact that men and women tend to be employed in different jobs explains a large share of the earnings differential between the sexes. Surprisingly, occupational age segregation has received little attention in the social science literature (for a recent exception see MacLean, 2006). To the best of my knowledge, its effect on the earnings differentials between age groups has never been analyzed.

Why does occupational age segregation exist? As new occupations emerge in the economy, younger workers are more likely to be employed in these new occupations. One of the reasons for this is that younger employees acquired their educational qualifications more recently and have the skills necessary to work with new technologies. An obvious example would be computer programmers. Most educational institutions introduced programming in their curricula only recently, and therefore students who graduated in the last twenty years are more likely to possess skills and qualifications necessary to take the job of a software programmer.

Then, younger people have higher levels of job mobility. Older people tend to have more firm-specific experience and, therefore, are less likely to be dismissed or leave the firm voluntarily. Besides, older workers are more likely to have families and other social ties that make them more risk-averse. Age and firm-specific experience increase the costs of job mobility. Thus, younger workers have a higher probability of moving to new occupations.

Segregation may arise not only at the occupational level, but also at the level of industries or jobs. More generally, if there are two sectors of the economy, the new and the old, then employees in the new sector will tend to be younger than employees in the older sector.

Now let us assume that earnings in the new sector are higher than in the old sector. The new sector can be more technologically advanced and have higher productivity. Also, new jobs are likely to emerge in expanding industries and enterprises that are more economically successful.

If younger workers have a higher probability of being employed in the new sector and the earnings in this sector are higher than in the old one, this will affect the shape of the age-earnings profile. The direction of the effect will be opposite to what is predicted by Ben-Porath's model of the accumulation of human capital over the life cycle. Under these conditions, earnings would "peak" earlier than in a situation in which age segregation did not exist.

If age segregation is not large or the differential in earnings between the new and old sectors is small, the effect on the shape of the age-earnings profile will be modest. However, if age segregation increases as a result of a rapid structural economic change and the earnings in the new sector are considerably larger than in the old one, the shape of the age-earnings profile will be affected more seriously.

Finally, age-earnings profiles in Russia can be affected by the class composition of the Russian labour force. Goldthorpe and McKnight (2006) compared the cross-sectional age-earnings profiles in the UK for men in different classes. They found that in non-manual classes with a service contract older men earn much more than younger men, while in manual classes with a labour contract this difference between age groups is smaller. Manual classes are paid per performance and their earnings directly depend on productivity that increases little with age and may even decrease. Non-manual classes, on the contrary, are on the career ladder and have higher chances of being promoted in an older age. Hence the difference in the shape of age-earnings profiles.

It was shown in chapter 3 that class composition in Russia is different from that of Western countries, especially for men. There is a higher proportion of men employed in manual jobs in Russia compared with Western Europe. If Goldthorpe's theory holds in Russia, this can affect the shape of age-earnings profiles so that the difference between the average earnings of older and younger men is smaller. I test this hypothesis in section 4.8.

In this chapter I first present cross-sectional and longitudinal age-earnings profiles for Russia and then discuss what explanations are consistent with the evidence, with a special focus on the effects of occupational age segregation and class composition.

4.4 Data and methods

The best possible data for age-earnings profiles come from labour force surveys where the sample size is large enough to estimate mean earnings for each one-year age group. The Russian Statistical Office conducts labour force surveys four times a year. Unfortunately, the individual-level data from these surveys are not available for public access. Therefore, to construct age-earnings profiles I use the data from the RLMS. The age-earnings profile for 1991 is based on the data from the GSS-USSR (Swafford et al., 1995). To construct the age-earnings profiles for men in the USA and Britain, presented in Section 4.1, I used respectively the data from the 2006 March Current Population Survey and the 2006 Labour Force Survey. The descriptions of these data sets are available on the websites of the US and UK statistical offices.[3]

The crucial variables for the analysis are age and earnings. Coding age in all data sets is straightforward. For earnings, in the RLMS I use the variable for after-tax earnings received at the primary job in the thirty days preceding the survey. The phrasing of the GSS-USSR question about earnings is similar to the RLMS.[4]

[3] `http://www.census.gov/cps/` and `http://www.statistics.gov.uk/statbase/Source.asp?vlnk=358&More=Y#general`.

[4] To construct all the profiles, I use the data on actual rather than contracted earnings. It may

The sample was stratified by sex, with separate profiles constructed for men and women. In all further analysis I limit the sample to men aged twenty-two to sixty and women aged twenty-two to fifty-five. The inclusion of people under twenty-two would strongly bias the sample towards the less educated people who enter the labour market earlier. In Russia, students usually start university education when they are sixteen and an average university course lasts for five years. By age 22 most people finish full-time education and enter the labour market. The official age of retirement for men is sixty and for women fifty-five years.

There are several ways to construct cross-sectional age-earnings profiles. First, it is possible to calculate mean earnings for each one-year age group, then plot the mean values and connect them with the line. This would be equivalent to regressing earnings on a series of dummies for each one-year age group (i.e., the saturated model). This method works well with large samples, but with smaller samples it is not very efficient. A possible solution is to calculate mean earnings for larger age groups. However, in this case the profile would be a step function.

Another approach is to regress earnings (or logged earnings) on age and age squared, as usually done in Mincer-type models. This method implies a certain functional form for the age-earnings association, and the rise of earnings in early age is assumed to be symmetric to their decline in older age. The use of the quadratic function to model the association between age and earnings was previously criticized in the literature (Murphy and Welch, 1990; Robinson, 2003). In our case, this may be particularly misleading. As shown in Section 4.5, in some years the shape of age-earnings profiles in Russia is very far from being symmetric.

To correct for this, higher order polynomials for age can be added to the model.

be argued that wage arrears that were widespread in Russia in the late 1990s, could affect the shape of profiles. Gerber (2006) shows that the association between work experience (calculated as age minus the years of education minus six) and wage arrears is non-linear. The employees with the least and the most work experience (i.e., the youngest and the oldest) experienced more arrears. To check for the robustness of the results, I constructed the age-earnings profile for 1998, the year when the wage arrears were at their maximum, with the data on contracted rather than actual earnings. The shape was the same as the shape of the profile constructed with the data on actual earnings.

Alternatively, it is posible to use a nonparametric approach that does not imply any functional form for the age-earnings association. This method is well known in the economic literature (Card, 1999) and sociology (Fox, 2000a,b; Andersen, 2009). Formally,

$$\log earn_i = f(age_i) + \varepsilon_i \tag{4.1}$$

where $f(age_i)$ is a function that is estimated locally at some focal point of age. There are two main types of estimators that can be used to estimate $f(age_i)$: local polynomial regression and splines (Fox, 2000b; Keele, 2008). While mathematically different, in practice in most cases they produce similar smooths. I construct cross-sectional age-earnings profiles with both methods, using the R package `mgcv` and the command `loess`.[5]

The main advantage of nonparametric models is flexibility. The analyst does not have to make any assumptions about the functional form of the association between two variables (although it is assumed to be smooth). The disadvantage of nonparametric regression is that, in contrast to ordinary OLS regression, it does not produce two parameters (the coefficients for the intercept and the slope) that describe the association. Hence nonparametric regressions should be analyzed visually.

Nonparametric regression can be extended to include several predictors (Fox, 2000a; Keele, 2008; Andersen, 2009).

$$\log earn_i = f(age_i, x_i) + \varepsilon_i, \tag{4.2}$$

where x_i is a control variable. However, model 4.2 becomes difficult to estimate

[5]Some nonparametric regression models can be fitted in Stata with the commands `lowess`, `lpoly`, `running`, or for multivariate analysis, with the commands `mlowess` and `mrunning`. However, R provides a larger number of more versatile tools for fitting and interpreting nonparametric regressions. In particular, semiparametric models that I use to construct class-specific profiles are more easily estimated in R with the command `mgcv`. At the moment, Stata's ability to fit semiparametric models with the command `mrunning` is quite limited.

when it includes more than three predictors, as it requires a very large sample size. (Even in the case of two predictors think of a three-dimensional space that is divided into small "cubes", and each of these cubes should contain enough observations to allow for the estimation of local regression). Besides, model 4.2 with several predictors is hard to visualize.

Model 4.2 can be modified into a more restrictive additive model.

$$\log earn_i = b_0 + f(age_i) + f(x_i) + \varepsilon_i, \tag{4.3}$$

This model does not allow for the interactions between *age* and x, but it is easier to estimate and interpret. Furthermore, we can assume that x is associated with the dependent variable (in our case, logged earnings) parametrically. This would yield a semiparametric model:

$$\log earn_i = b_0 + f(age_i) + b_1 x_i + \varepsilon_i, \tag{4.4}$$

The association between age and earnings may change, conditional on x. For instance, the age-earnings profiles for social classes may look different. Therefore, to construct class-specific profiles, we may want to allow for the interactions between age and parametric terms.

$$\log earn_i = b_0 + f_1(age_i) + b_1 x_i + f_2(age_i) x_i + \varepsilon_i, \tag{4.5}$$

For longitudinal profiles, I use five-year birth cohorts and have enough observations to calculate the median earnings for each cohort in a given year. I construct longitudinal profiles by simply connecting these median values. In this case, using nonparametric regression is unnecessary. Besides, it would be problematic as the observations for the years 1997 and 1999 are missing.

4.5 Cross-sectional age-earnings profiles

Figures 4.2 and 4.3 show cross-sectional age-earnings profiles for men and women. The solid lines are the spline smooths and the dashed lines show the 95% confidence bands around them. The dotdash lines are the estimates from local polynomial regression.

The y-axis on the left of the figures shows earnings in the nominal prices for each year. The y-axis on the right shows real earnings as a percentage of the median earnings in 2006, for men and women in the 22 to 60 and 22 to 55 age groups, respectively. To calculate real earnings I used the official deflator.[6]

I use monthly earnings rather than hourly wage as the dependent variable. People in Russia usually think in terms of monthly earnings, and this is how the question about earnings was asked in the RLMS. It is also possible to create a variable for hourly wages with the RLMS data, as there are variables for the number of hours worked both weekly and in the last month. However, these data are not very reliable. The variables contain many values that are out of the range of what is possible, as well as many missing values. [7]

Age-earnings profiles do not include people who are currently not in the labour force. The youngest and the oldest workers have the higher probabilities of being unemployed. To check whether the difference in the unemployment rates across

[6] It can be argued that it would be more logical to use 1991 as the reference year. I have chosen 2006 for several reasons. The GSS-USSR sample for 1991 represents the European USSR and, therefore, is not entirely comparable with the RLMS data for Russia. This is the reason why the graphs for 1991 do not have the right y-axis. To the best of my knowledge, the GSS-USSR is the only source of individual data on earnings for the USSR. The use of the official data on earnings in 1991 provided by the Russian Statistical Office can be misleading. First, the Russian Statistical Office used the data provided by enterprises rather than self-reported earnings. Second, the definition of earnings is different compared to the RLMS. Third, it is not possible to get estimates for mean and median earnings for the age groups that I use in this paper. Also note that because of high inflation in 1992 and 1993 the estimates of real earnings for these years are approximate.

[7] To check if measuring earnings on the hourly rather than monthly basis changes the shape of age-earnings profiles, I constructed a variable for the hourly wage for men by dividing the monthly earnings by the number of hours worked weekly, multiplied by 4.2. The top and bottom 5% of observations were removed. Generally, the age-hourly wage profiles look similar to the age – monthly earnings profiles. However, the confidence bands are wider and the profiles are less robust.

the age groups changes the shape of the profiles, I assigned earnings equal to 0.5 to all working age men who were not in the labour force.[8] The resulting profiles look similar to those presented in Figure 4.2, although the average earnings of the youngest and the oldest workers are relatively lower compared to middle-aged men.

Let us first look at the results for men. In 1991, before the dissolution of the USSR and the beginning of the rapid economic reforms in Russia, the profile has a parabolic shape, with the average earnings peaking at the age of about 40. The shape of the profile remains similar in 1992 and 1993, in the early years of the reforms, although the decline in earnings at an older age becomes steeper than their increase at a younger age.[9]

In 1994 and 1995 the shape of the profile changes. There is almost no difference in the average earnings of men under 45, but after this age average earnings decrease steeply. Note that for these years the usual quadratic specification of the age-earnings association would give especially misleading estimates.

In 1996 the profile goes back to the parabolic shape, but average earnings peak earlier than at the beginning of the 1990s. The data for 1997 and 1999 are missing. In 1998, the year of a major economic crisis in Russia, the profile looks similar to 1994 and 1995. In 2000 to 2006 the profile again takes the parabolic shape, with average earnings peaking at the age of about 35 years.[10]

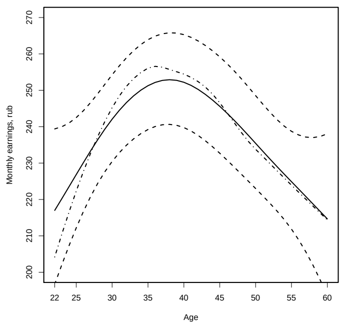
The analysis of the cross-sectional age-earnings profiles for men leads to several conclusions.

1. In the beginning of the 1990s and in the 2000s, the shape of the profile is

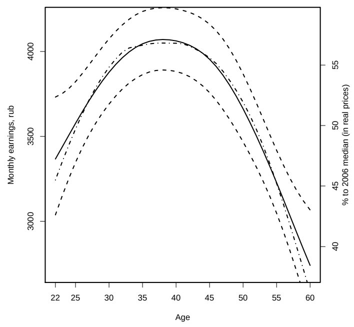
[8] As in the case with hourly wages, I conducted this test only for men.

[9] The words “increase” and “decline” are used as convenient metaphors throughout this chapter when I discuss cross-sectional profiles. It is a common mistake to interpret cross-national age-earnings profiles in terms of the growth or decline of individual earnings (Thornton et al., 1997). This can only be done with the longitudinal profiles that will be presented in the next section.

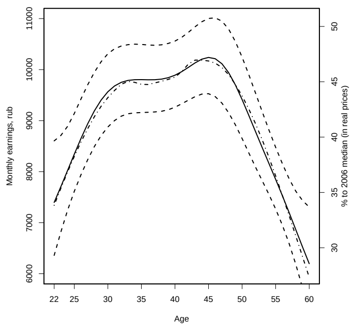
[10] In 2003, the spline and local polynomial smooths give somewhat different results. The spline regression is possibly oversmoothed.



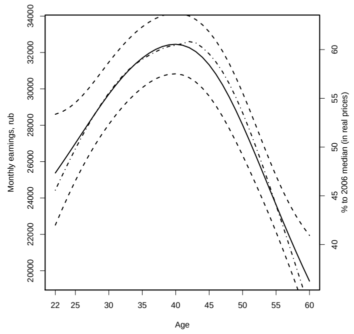
(a) April - May 1991, n=857



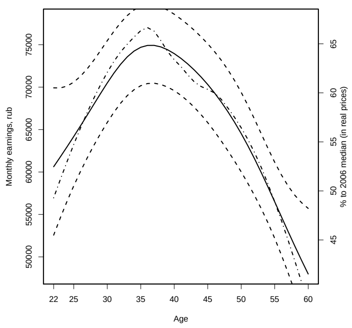
(b) July - October 1992, n=3121



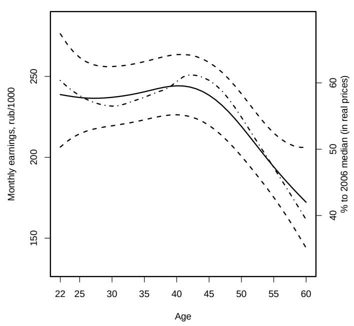
(c) January - April 1993, n=2639



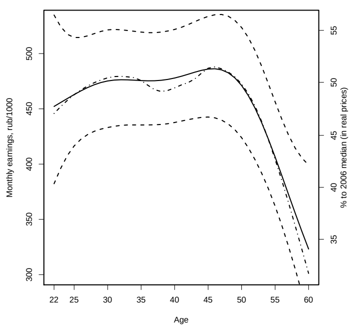
(d) June - August 1993, n=2618



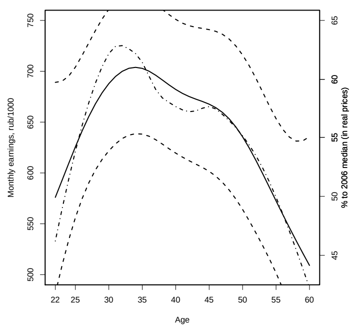
(e) October 1993 - January 1994, n=2028



(f) Autumn 1994, n=1582

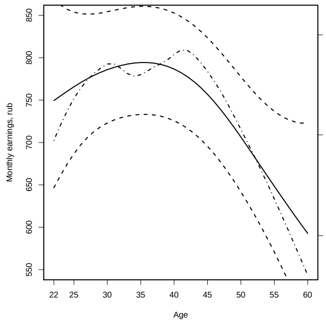


(g) Autumn 1995, n=1382

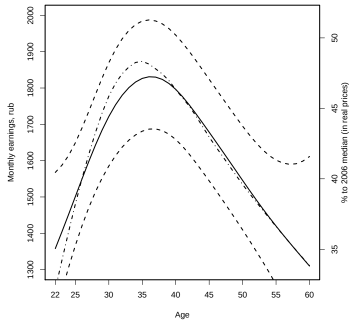


(h) Autumn 1996, n=1134

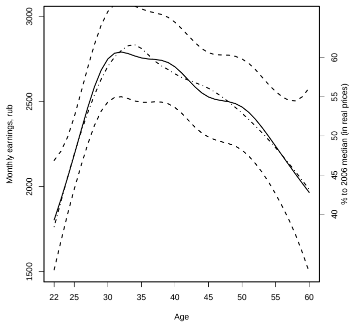
Figure 4.2: Age-earnings profiles, Russia (1991 - the European USSR), 1991-96, men aged 22 to 60, the RLMS (except (a)). The solid lines represent the spline smooths with the 95% confidence bands (the dashed lines). The dotdash lines represent the local polynomial regression estimates.



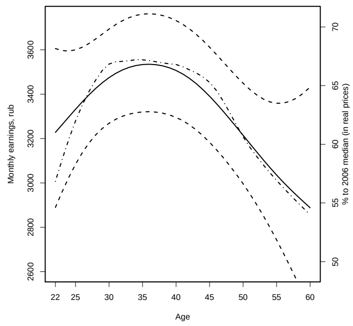
(i) 1998, n=1217



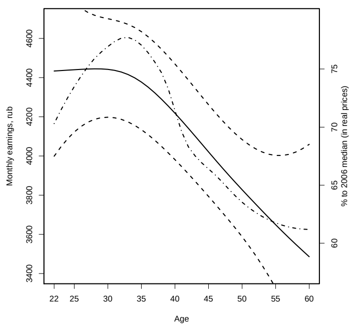
(j) 2000, n=1515



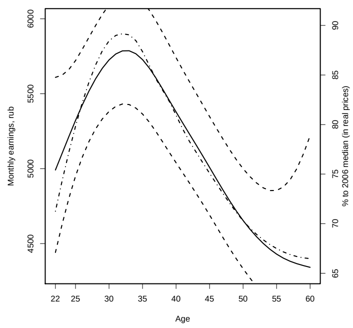
(k) 2001, n=1734



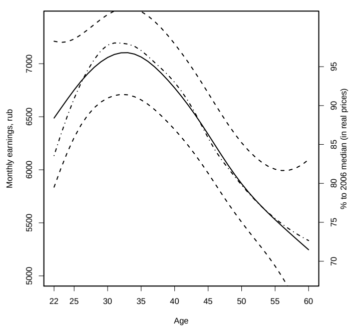
(l) 2002, n=1861



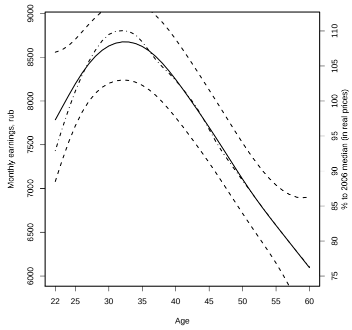
(m) 2003, n=1932



(n) 2004, n=2059

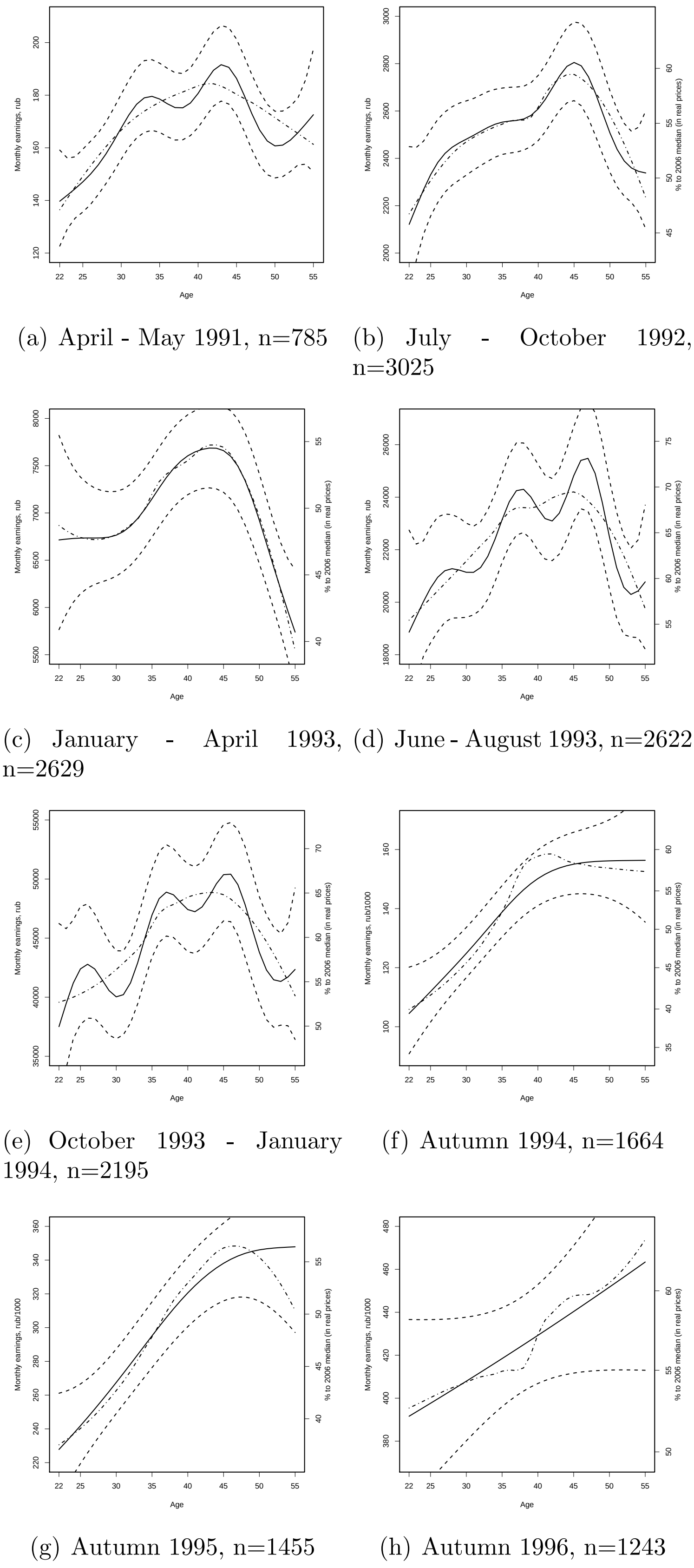


(o) 2005, n=2051



(p) 2006, n=2525

Figure 4.2: Age-earnings profiles, Russia, 1998-2006, men aged 22 to 60, the RLMS (all surveys conducted in the autumn) (cont.).



(a) April - May 1991, n=785

(b) July - October 1992, n=3025

(c) January - April 1993, n=2629

(d) June - August 1993, n=2622

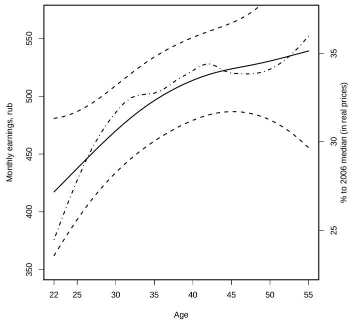
(e) October 1993 - January 1994, n=2195

(f) Autumn 1994, n=1664

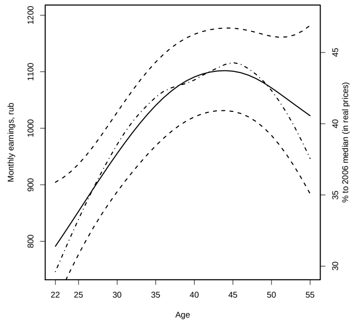
(g) Autumn 1995, n=1455

(h) Autumn 1996, n=1243

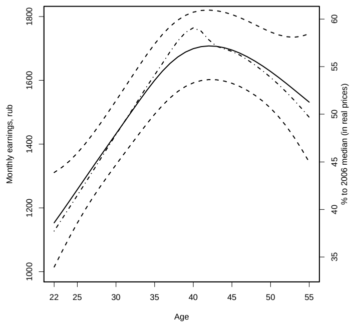
Figure 4.3: Age-earnings profiles, Russia (1991 - the European USSR), 1991-96, women aged 22 to 55, the RLMS (except (a)). The solid lines represent the spline smooths with the 95% confidence bands (the dashed lines). The dotdash lines represent the local polynomial regression estimates.



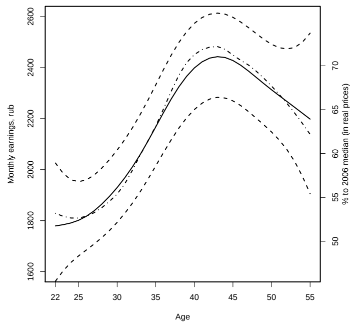
(i) 1998, n=1297



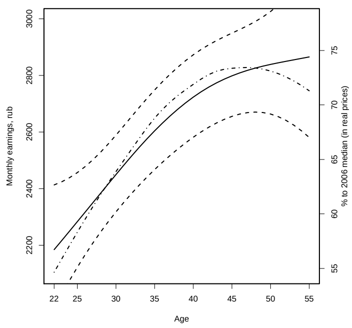
(j) 2000, n=1661



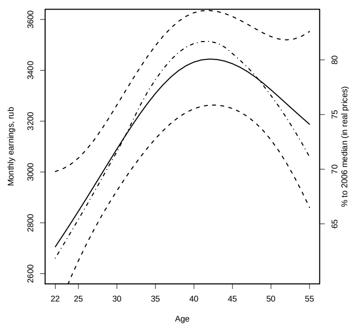
(k) 2001, n=1938



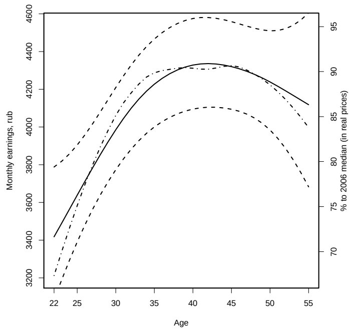
(l) 2002, n=2047



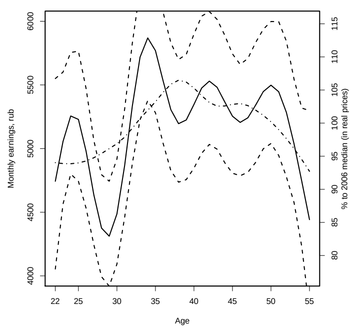
(m) 2003, n=2148



(n) 2004, n=2237



(o) 2005, n=2145



(p) 2006, n=2719

Figure 4.3: Age-earnings profiles, Russia, 1998-2006, women aged 22 to 55, the RLMS (all surveys conducted in the autumn) (cont.).

close to parabolic. In the 2000s, men's earnings peak earlier than in 1991-93. In both periods average earnings peak early compared to the 2006 profiles for Great Britain and the USA.

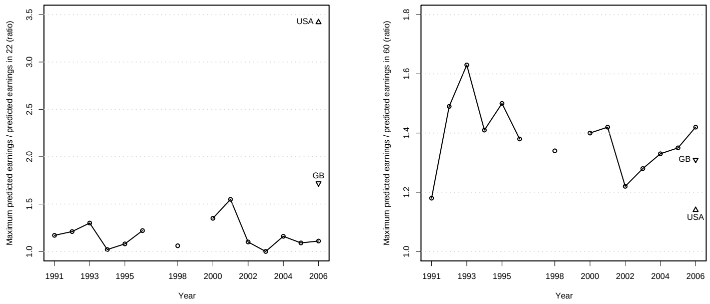
2. In the middle of the 1990s, the shape of the profile changes and there is no difference in the average earnings of men under 45. The profile for 1996 is more similar to the 2000s. The profiles for 1997 and 1999 are missing.

3. The difference in average earnings between the youngest men and men at the age of maximum average earnings is smaller in Russia compared to the USA and Great Britain. Figure 4.4(a) illustrates this point. On the y-axis I plot the ratio of maximum average earnings to average earnings at age 22. In 2006 maximum average earnings in Russia were larger than average earnings at age 22 by 11%, compared to 72% in Great Britain and 342% in the USA.

   The difference in the average earnings between the men at age 60 and men with the maximum average earnings, is larger in Russia than in the USA and Great Britain, but not by much (see Figure 4.4(b)).

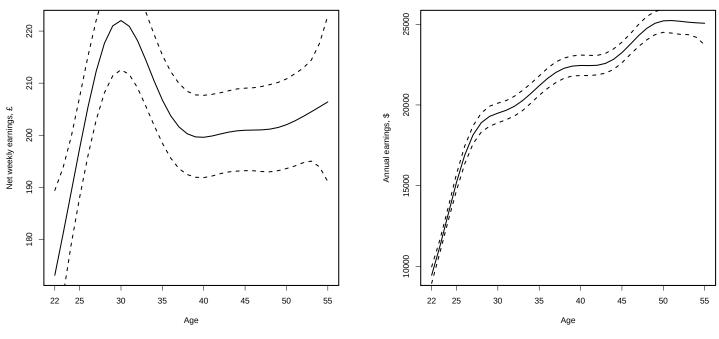
4. The proportion of the variance of earnings explained by age is smaller in Russia than in the USA and Great Britain. R^2 in the spline regression of logged earnings on age for men is 0.01 in Russia, 0.06 in Great Britain and 0.1 in the USA. In Russia age is a very weak predictor of earnings.

For women, local polynomial and spline regressions more often give different shapes of age-earnings profiles, with the splines probably being overfitted (especially for 2006). However, the trend is clear. In contrast to men, women's average earnings peak later, in most years at age about 45. The "rise" in earnings at a younger age is larger then their "decline" at an older age. In some years (1994, 1996, 1998, 2003), there is no "decline" in earnings at an older age at all.



(a) max/22 ratio (b) max/60 ratio

Figure 4.4: The ratios of maximum average earnings to average earnings at 22 (a) and at 60 (b), men. The ratios are based on spline smooths.



(a) Great Britain, LFS 2006, n=5709 (b) The USA, CPS March 2006, n=39275

Figure 4.5: Age-earnings profiles, women aged 22 to 55, nonparametric spline scatter plot smooths with the 95% confidence bands (dashed lines)

Compare these results with the age-earnings profiles for women in the USA and Britain (Figure 4.5). The profiles for Russia and the USA have similar shapes, although the age premium in earnings is much larger in the USA than in Russia. In Britain, however, the profile is different and women's average earnings after age 30 are smaller than at age 30. This can probably be explained by the higher prevalence of part-time work among women in Britain. R^2 in the models for women is under 0.04 for all three countries, which indicates that age is a weak predictor of earnings for women.

The analysis of the cross-sectional age-earnings profiles in Russia raises several questions. Why do men's earnings in Russia peak earlier than in Western countries? What caused the change in the shape of age-earnings profiles in Russia in the middle of the 1990s? Why do women's average earnings not peak as early as men's?

Before discussing these questions, I present longitudinal age-earnings profiles.

4.6 Longitudinal age-earnings profiles

In the previous section I constructed cross-sectional age-earnings profiles for the period from 1991 to 2006. Another way to look at the age-earnings association is to analyze the dynamics of earnings for separate birth cohorts in the longitudinal perspective. Several studies have shown that the shape of longitudinal age-earnings profiles may differ from cross-sectional ones. In the longitudinal perspective, the decline of earnings at an older age is rarely observed. This is frequently explained by inflation and the rise of average real earnings over time.

To construct longitudinal profiles I used five-year birth cohorts. Figures 4.6 and 4.7 show longitudinal profiles for men and women. Cohort-specific median earnings are plotted on the y-axis. Earnings were adjusted for the inflation at the level of 2006. I begin the profiles in 1994, as calculating real earnings for 1992-93

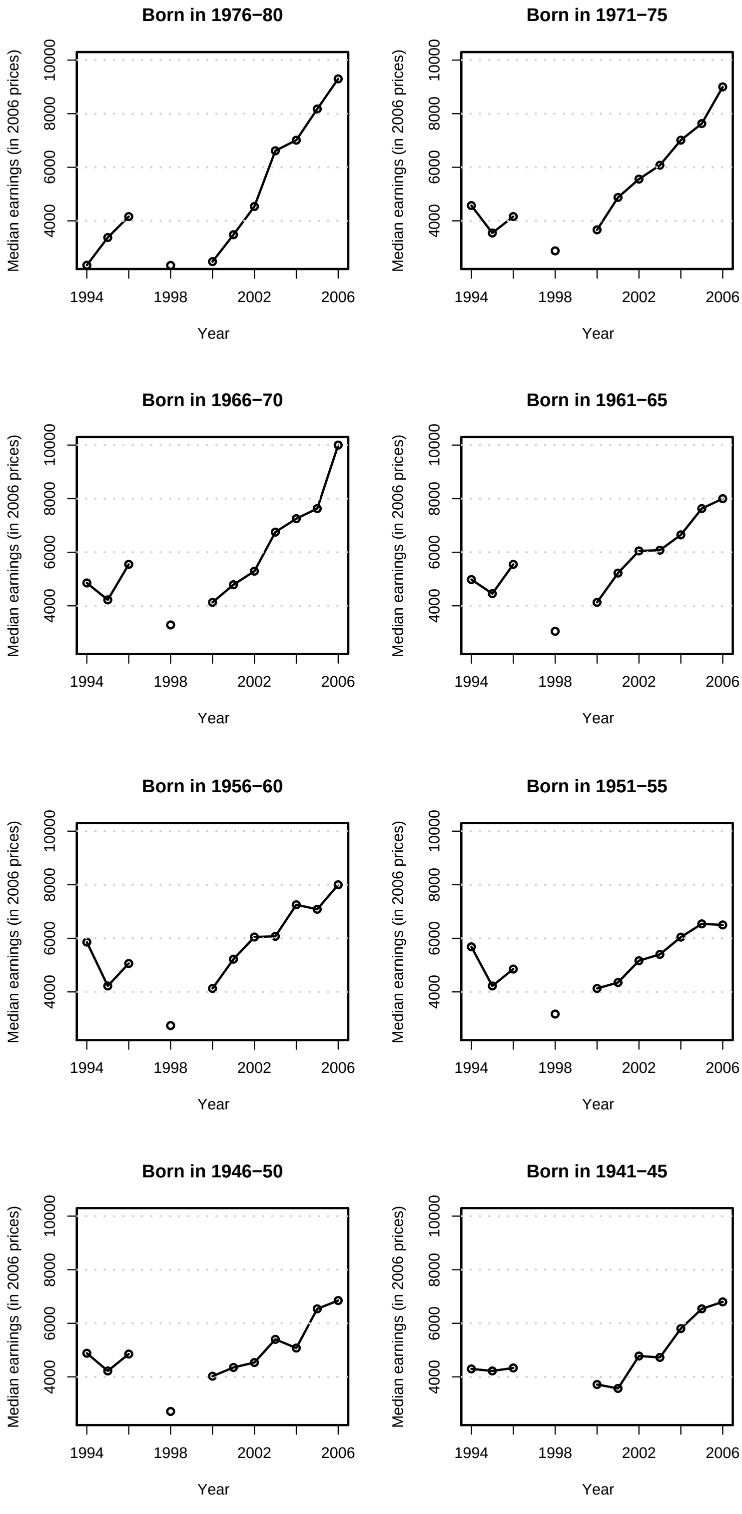


Figure 4.6: Longitudinal year-earnings profiles for five-year birth cohorts. Earnings adjusted for inflation at the 2006 level. Men, RLMS, 1994-2006

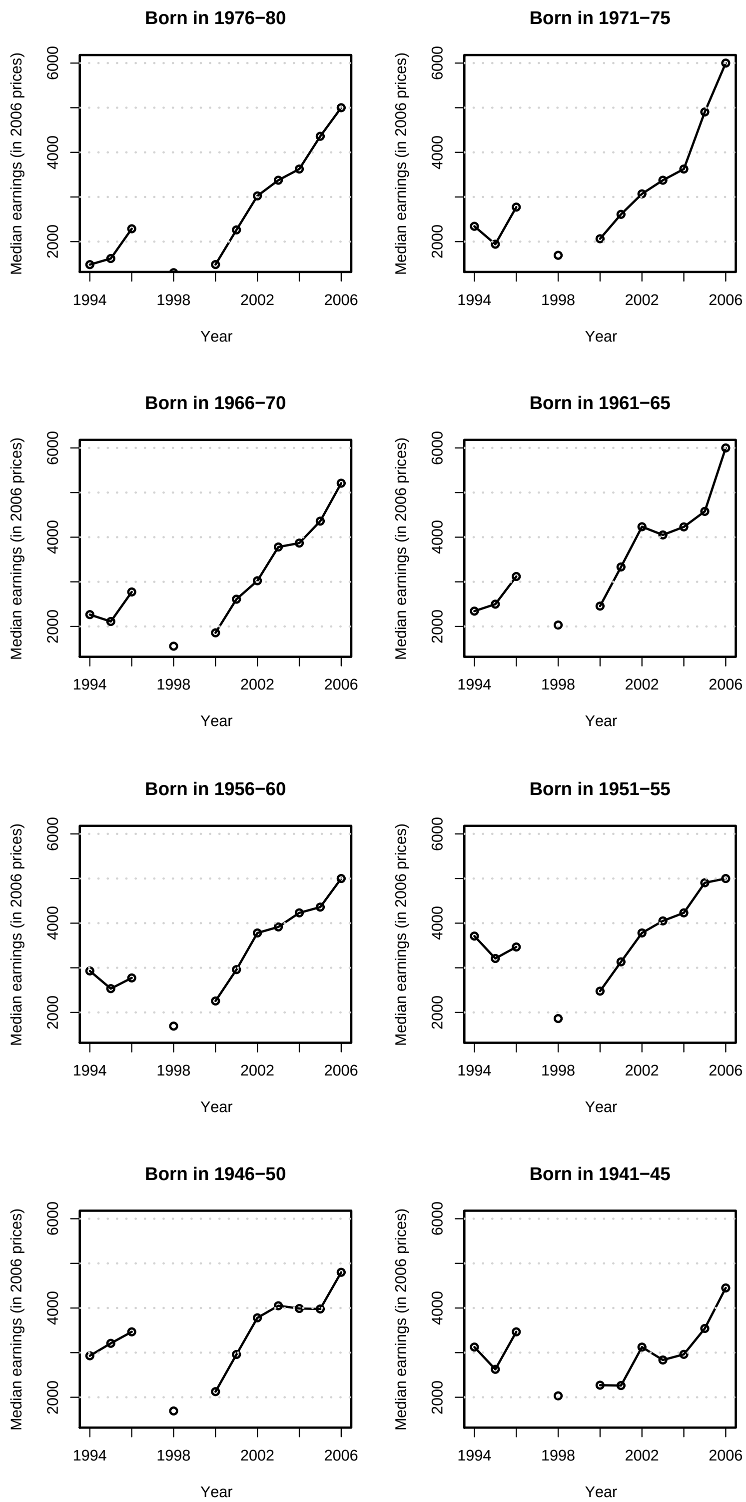


Figure 4.7: Longitudinal year-earnings profiles for five-year birth cohorts. Earnings adjusted for inflation at the 2006 level. Women, RLMS, 1994-2006

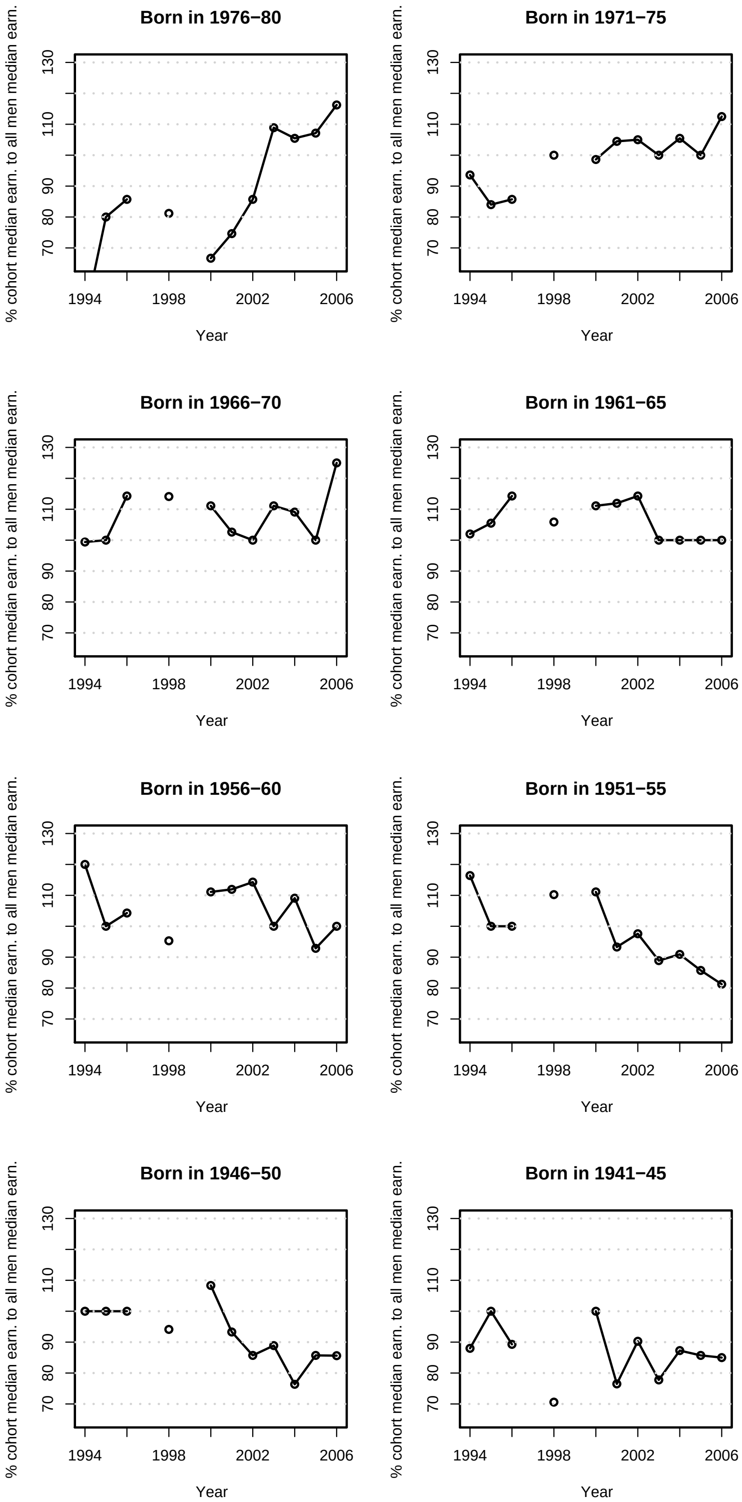


Figure 4.8: Longitudinal relative earnings profiles for five-year birth cohorts. The y-axis shows the ratio of the cohort-specific median earnings to the median earnings of men at age 22 to 60 (multiplied by 100). Men, RLMS, 1994-2006

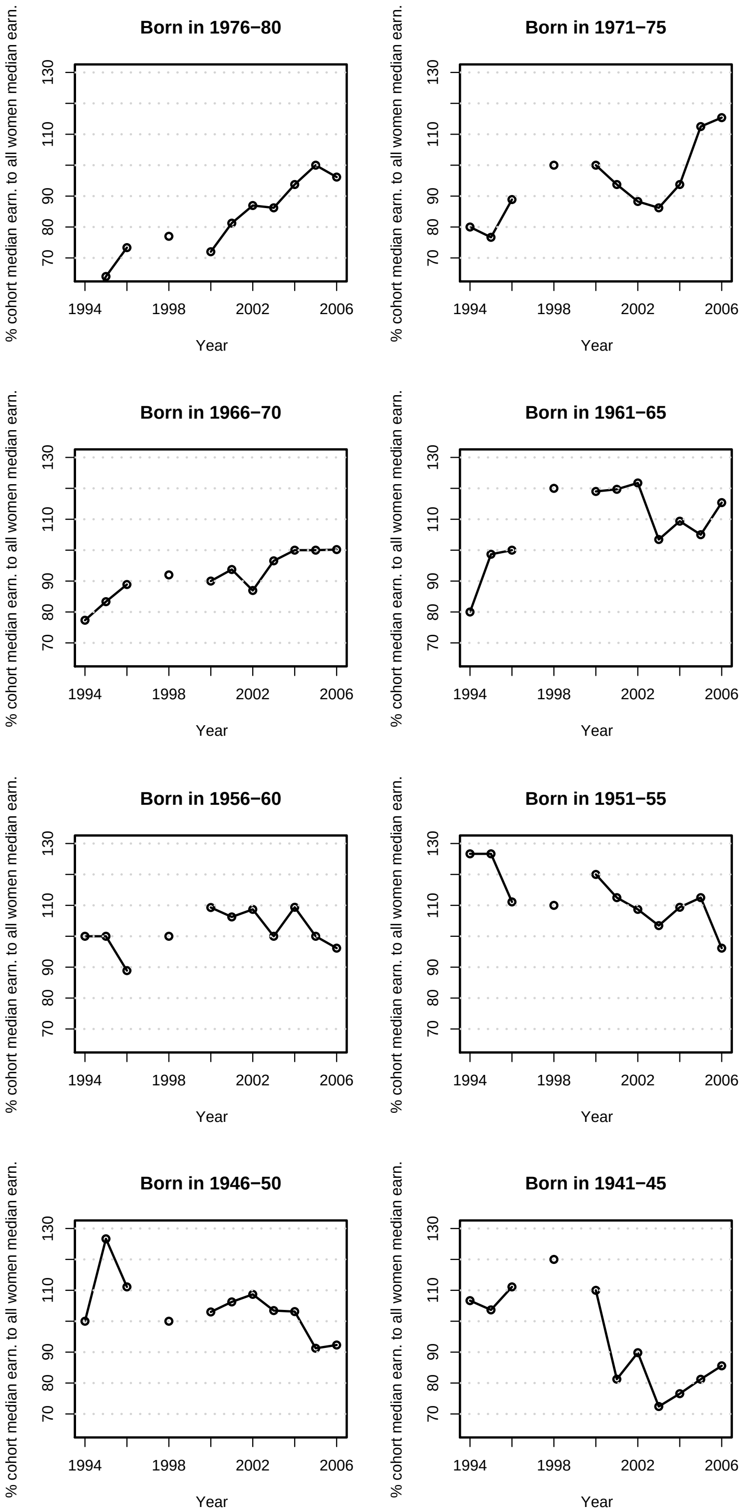


Figure 4.9: Longitudinal relative earnings profiles for five-year birth cohorts. The y-axis shows the ratio of the cohort-specific median earnings to the median earnings of women at age 22 to 55 (multiplied by 100). Women, RLMS, 1994-2006

with the RLMS Phase I data is too error-prone because of high inflation in that period.

The profiles for most cohorts follow the same trend. The real earnings decreased from 1994 to 1995 and then slightly increased in 1996. The data for 1997 are missing in the RLMS, but according to the official data, in 1997 real earnings increased compared to 1996. In 1998 Russia experienced a major economic crisis and real earnings declined dramatically. The economic recovery started in 1999 and, as shown on the graphs, from 2000 to 2006 real earnings increased for all the cohorts. However, younger men experienced a much steeper growth than men in older cohorts. This is not the case for women, for whom real earnings increased more evenly over all the cohorts.

This pattern is more clear in Figures 4.8 and 4.9 where I plot cohort-specific relative rather than real earnings, for men and women respectively. The y-axis shows the ratio of cohort-specific median earnings to median earnings of all men aged 22 to 60 (or, for women, aged 22 to 55), multiplied by 100. If the relative median earnings of a particular cohort equal 100 that means that in this year the median earnings of this cohort were equal to the median earnings of all workers. If this value is 120, then the cohort-specific median earnings are 20% higher than the median earnings of all workers, etc.

As shown in Figure 4.8, for men the youngest cohorts, born in 1966-80, were the most successful in the post-Soviet period. For most of the 2000s, their relative median earnings were over 100 (i.e., higher than the total median earnings for men). The relative median earnings of the cohorts born in 1956-65 were also over 100 for most of the period; however, they tended to decline in the 2000s. Men born in 1941-55 were the least successful, and their relative earnings were in decline during the period.

For women the picture is different. The relative earnings of the three youngest cohorts, born in 1966-80, were under 100 for most of the period, although they had a tendency to increase. The relative earnings of middle-aged women, born in 1946-65, were decreasing in the 2000s, but remained well over 100. Only for the oldest women, born in 1941-45, were relative earnings under 100 in the 2000s.[11]

4.7 Age segregation in the labour market and earnings

The goal of this section is to produce evidence in support of the hypothesis about the effect of occupational age segregation on the shape of age-earnings profiles presented in section 4.3. First, I discuss the characteristics of the labour market in post-Soviet Russia that are essential for understanding the association between age and earnings. Then I present quantitative evidence from the RLMS in support of the hypothesis about the effect of age segregation in the labour market on age-earnings profiles.

In chapter 1 I discussed the development of the labour market in post-Soviet Russia and its main characteristics. Although wage differentiation existed in the USSR, the pay of workers was relatively equalized. After the introduction of market reforms, wage differentiation skyrocketed. The privatization of old Soviet enterprises and the emergence of new firms created the private sector of the economy. Average earnings were higher in the private sector compared to the state sector. The rapid structural reforms in the economy led to the massive reallocation of the labour force that moved between sectors, occupations and jobs (Sabirianova, 2002).

There were several flows of job mobility that need to be separated. First, workers from traditional enterprises were moving to new private enterprises, mainly in trade and services. The most skilled and productive employees were often the first to change jobs. Gimpelson and Lippoldt (1999) and Clarke and Kabalina (2000)

[11]Note that this is a very small and specific cohort born during WWII.

present evidence that men and younger workers had a higher probability of being employed in the new private sector where the pay was higher. At the same time, enterprises in the old traditional sectors, especially those that were less economically successful, had problems with hiring the young labour force. Clarke wrote that "very few young people are willing even to consider working in an industrial enterprise for the wages on offer, and few stay for long" (Clarke, 1999, p.95).

Second, workers were migrating between enterprises in the old state and privatized sectors. More successful enterprises were in a position to attract better workers. Depressed enterprises accumulated the low quality labour force, including elderly workers who had little incentive to move elsewhere. Clarke called this process "the polarisation of industrial enterprises" (Clarke, 1999, p.125). The polarisation was not stable, as the fortunes of enterprises were changing rapidly. In the conditions of high economic and political instability, the situation, even in the most successful enterprises, could easily deteriorate within several years. The best workers were moving from one firm to another as long as they could find a job with better pay. Firm-specific work experience was not rewarded (Maltseva, 2007). This is hardly surprising given that the people who stayed at the same enterprise for a long time were often those who lacked skills to find a better job elsewhere.

The students of the Russian labour market noticed that wages in Russia were strongly affected by the performance of firms (Clarke, 1999; Gimpelson and Kapeliushnikov, 2007). The earnings of employees who were performing the same job in two enterprises in the same branch and the same region, could differ significantly depending on the economic fortunes of the enterprise. Standard Mincer-type models explain less variance in earnings in Russia than in Western countries. It is likely that this can be explained by a larger firm-specific component in earnings.[12] Qualitative evidence shows that workers in more successful enterprises in

[12]Large unexplained variance in earnings equations is hardly specific to Russia and is also characteristic of Western countries. Bowles et al. (2001) try to explain this with the behavioural

the old sector tend to be younger than workers in depressed enterprises.

The fact that younger workers were collected in the more successful sectors and firms can be analyzed from the perspectives of both supply and demand. On the supply side, younger workers were more likely to be actively looking for better jobs and ready for job mobility if there was a chance for it. People often tend to compare themselves with peers in the same age group. As the old and depressed sectors were aging, younger workers could avoid them not only because of low wages and wage arrears, but also because they were commonly regarded as jobs for the older generations. Older workers, and in particular women, more often avoided changing jobs, a decision that always involves some risk. As it was harder to find a new job for older people, the costs of failure were higher for them. Besides, some older people were contemptuous of employment in the sectors such as services and trade that had been frowned upon in Soviet times.

On the demand side, employers often preferred to hire younger workers, especially men. This tendency was particularly clear in the new private sector. Employers considered younger people to be more adaptable and flexible. These characteristics were particularly important in the uncertain and risky environment of post-Soviet Russia. Another reason for the preference for younger men could be their better health when compared with older men. Besides, most of the new Russian entrepreneurs were young or middle-aged themselves and, as hiring was often done through informal networks, the entrepreneurs were more likely to hire people in the same age group.

There are three levels at which age segregation in the labour market was hap-

approach to the determination of earnings. According to their argument, apart from human capital, employers reward specific psychological attitudes and behaviours. This argument is probably even more relevant to the Russian case. The interviews with employers in the new private sector showed that they often paid more attention to the attitudes such as, for example, loyalty than to formal qualifications. As the general director of a private firm said, "decency is more important for me than professionalism" (Clarke, 1999, p.152). In many enterprises, the basic pay was lower than bonuses that were paid at the discretion of foremen and supervisors. This was used as a tool of managerial control over employees. In practice, the bonus system could lead to a high degree of subjectivity in the determination of earnings and high within-firm earnings differentials.

pening: economic sectors, occupations and jobs. Unfortunately, with the RLMS data it is impossible to test quantitatively the hypothesis that occupations and jobs with a younger labour force were characterized by higher earnings. The sample size in the RLMS is too small to reliably estimate mean earnings for particular occupations and the information on firm-specific characteristics is missing.

However, analysis at a less detailed level of the economic sectors is possible. To define the sectors of the economy, I use two variables. These are the type of ownership (state vs. private) and the year of the foundation of the firm, as reported by respondents. Firms are classified as state if they are owned by the state completely. Therefore, firms with mixed ownership are classified as private. The RLMS includes the question on the year of the foundation of the firm only in some rounds. Since 2003, this question was dropped, most likely because of the high non-response rate. I use the RLMS data for 2002, the last year when this question was asked. Using these two variable, I define seven groups of people: those working in the state enterprises founded before 1992, in the new state enterprises founded in 1992-2002, the privatized enterprises founded before 1992, the new private enterprises founded in 1992-2002, the self-employed or working for the self-employed, and those in the state and private sectors who did not know the year of the foundation of their enterprises.

Figures 4.10 and 4.11 show box plots that present age and earnings distributions within these seven groups for men and women. In fact, these plots present the same information as quantile regression of earnings (or age) on the sector of the economy, the year of the foundation of the firm and the interaction between these variables. The goal is to check if the sectors with the younger labour force had higher average earnings.

The width of the boxes on the plots is proportional to the square root of the number of observations in the groups. Notches represent the confidence intervals for medians. If the notches do not overlap there is strong evidence that the group medians in the population are different.

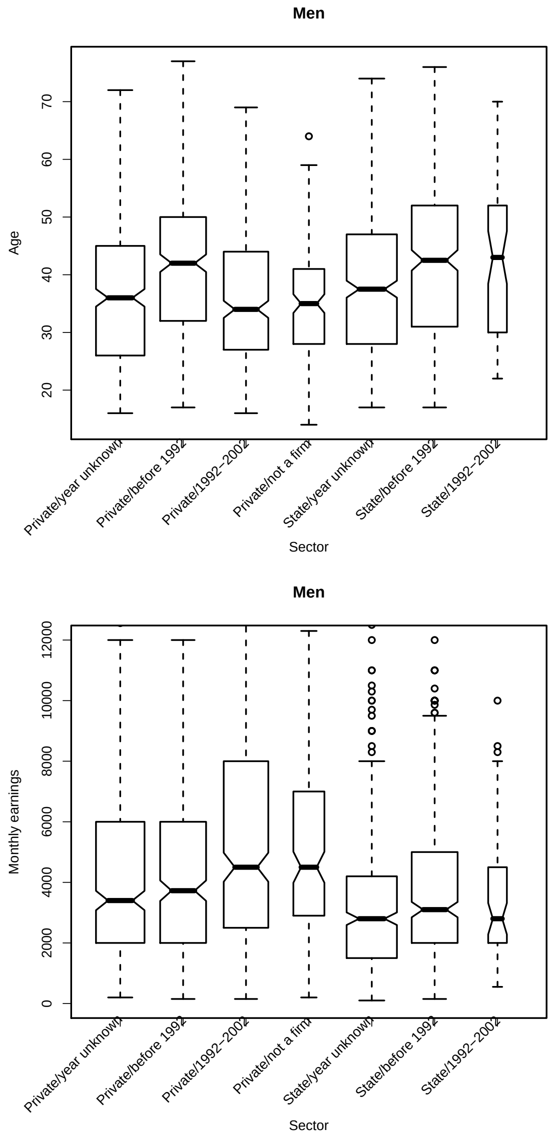


Figure 4.10: Age and earnings distributions by sectors of the economy. Men, RLMS 2002. The width of the boxes is proportional to the square root of the number of observations in the groups. Notches represent the 95% confidence intervals for medians. The outliers for earnings are not shown on the graph.

As can be seen from the figures, the new private sector and self-employment have a higher proportion of the youngest workers, both men and women. The median age of employees in these sectors is about 35. Workers in the state sector and in privatized enterprises tend to be older, with the median age over 40. The median age of women in the state enterprises founded after 1991 is relatively low,

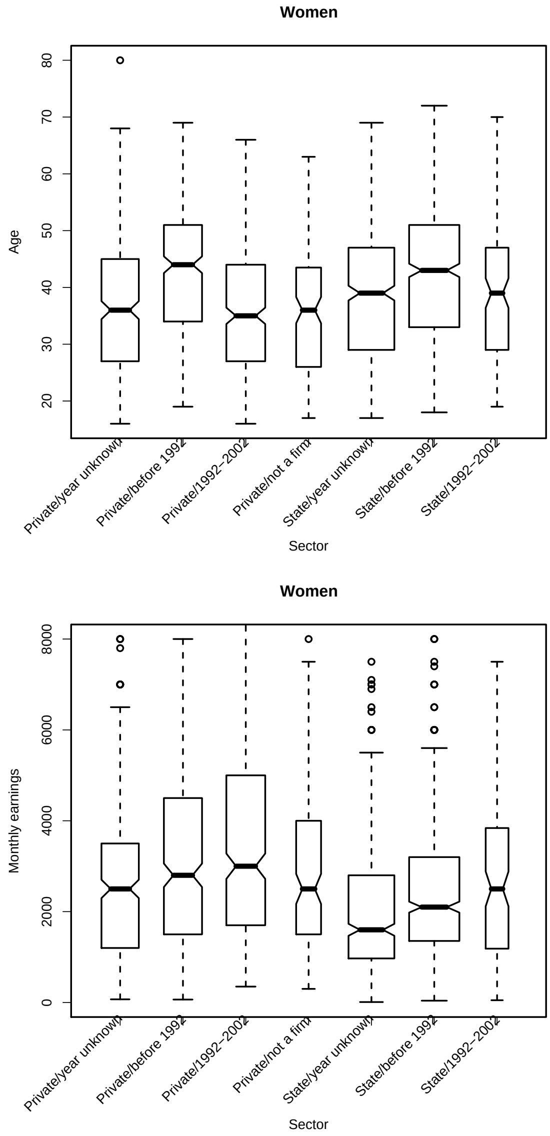


Figure 4.11: Age and earnings distributions by sectors of the economy. Women, RLMS 2002. The width of the boxes is proportional to the square root of the number of observations in the groups. Notches represent the 95% confidence intervals for medians. The outliers for earnings are not shown on the graph.

both in the private and state sectors. These results highlight the importance of making a difference between the privatized and new private sectors.

The median age of the workers who do not know the year of the foundation of their enterprises is almost as low as in the new private sector. This is hardly surprising as younger workers with less firm-specific experience are less familiar with the history of their enterprises. As indicated by the widths of the boxes, the proportion of those who did not answer the question about the year of the foundation of the firm is quite large. We do not know how these people are split between new and old enterprises and, admittedly, this introduces some selection bias. Unfortunately, this is inevitable with the data that are available. It is probably more likely that most of these people are employed in old enterprises. The older the enterprise, the more likely it is that the workers would not know the date of its foundation. If this is the case, this would make the age difference between the new private sector, on the one hand, and privatized and state enterprises, on the other hand, smaller. However, as follows from the graphs, even if all people in the "unknown" category worked in old enterprises, the difference in the median age between the new private sector and other enterprises would have still remained significant.

Now let us analyze the distribution of earnings. Both men and women employed in the private sector earn more than those in the state sector. For men, median earnings in the new private sector and in self-employment are much higher than in state and privatized enterprises. For women, the difference in median earnings between new private and privatized enterprises is smaller. The median earnings of self-employed women are not statistically significantly different from the median earnings in privatized enterprises and new state enterprises.

The earnings of people who do not know the year of the foundation of their enterprises are lower than the earnings in both old and new sectors. It is likely that these respondents have lower educational qualifications and are employed in occupations with lower pay.

The box plots confirm that younger men more often work in the sectors with higher earnings. For women, the pattern is less clear. While younger women are indeed more often employed in the new private sector, their earnings premium there is lower than for men.

Unfortunately, an analysis at the more detailed occupational level is not possible, but available evidence suggests that age segregation in the labour market is indeed one of the factors that explains the shape of the age-earnings profile. However, this cannot be the whole story as the shape of the cross-sectional profile for men in 1991, before the start of the market reform, was already different to Britain and the USA. Another factor that could affect the shape of age-earnings profiles is the class composition of the Russian labour force.

4.8 Occupational class and age-earnings profiles

In the previous chapter I have shown that occupational class composition in Russia is different to Western European countries and the USA, especially for men. The proportion of men employed in manual occupations is larger in Russia. If the shape of age-earnings profiles differs across the occupational classes, this can be one of the factors that explains the difference in the shape of the age-earnings profiles for Russian and Western European men.

Goldthorpe and McKnight (2006) showed with British data that non-manual and manual classes have different shapes of cross-sectional age-earnings profiles. Non-manual classes have greater variability of earnings across age groups than manual classes. In this section I check if this pattern holds in Russia.

Figure 4.12 presents class-specific cross-sectional profiles for Russian men in 2006.[13] Each subfigure shows a class-specific profile with 95% confidence intervals

[13] I omit the profile for the intermediate class (the smallest class for men in Russia) to fit the profiles on one page.

and also the profile for all Russian men aged 22 to 60 (shown with the dotdash line). To make the profiles visually comparable, each subfigure has the same y-axis scale. An additional advantage of the figure is that it allows to compare the average earnings across the classes. The profiles were constructed with a semiparametric regression that was described in section 4.4.

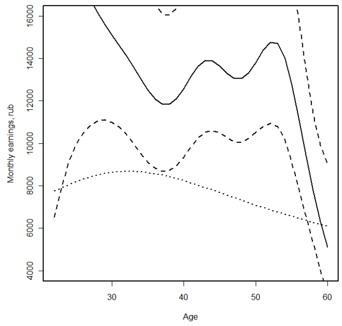
The profile for Russian male managers clearly looks different to what is observed in Britain. Young managers under age 30 earn the most (they are a small and self-selected group, so that the confidence intervals are large). After age 40 the average earnings "increase" until about age 50. The average earnings of managers over 50 are considerably smaller. This pattern probably reflects occupational age segregation, as younger and older managers are likely to be employed in different sectors of the economy, industries and enterprises.

The profile of higher professionals (mainly engineers, architects, doctors and university lecturers) is more symmetric, with earnings peaking at age about 40. Compared with the profile for all men, the maximum in earnings for higher professionals is at a later age. Lower professionals (army and police officers, technicians) have a non-linear profile, with men aged 25 to 35 and over 50 having the highest average earnings. The profiles for the self-employed and lower supervisors and technicians are similar to the one for higher professionals.

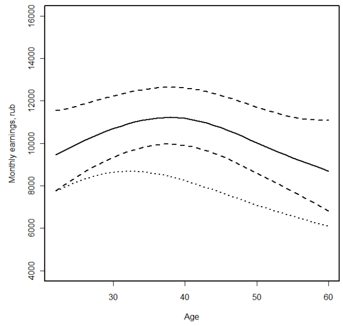
Three manual classes (lower sales and service, lower technical and routine) have similar profiles. The profiles are flat, with the average earnings of men under 40 being about the same. The earnings of older men are somewhat smaller.

Managers have the highest earnings, followed by higher professionals, the self-employed and lower supervisors. Lower professionals also have earnings that are above the average. Lower sales and service, lower technical and routine classes are below the average.

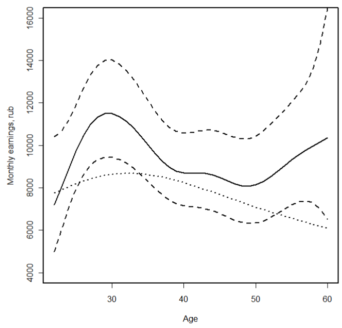
The examination of cross-sectional class age-earnings profiles for Russia shows that they are quite different from the British ones. Even for the non-manual



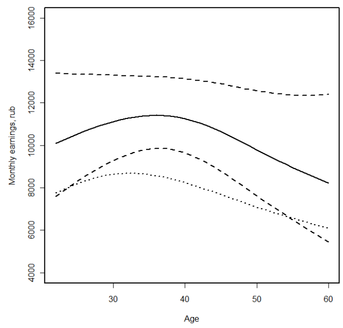
(a) 1a/2a.Managers



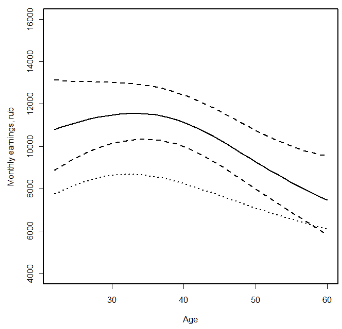
(b) 1b.Higher professionals



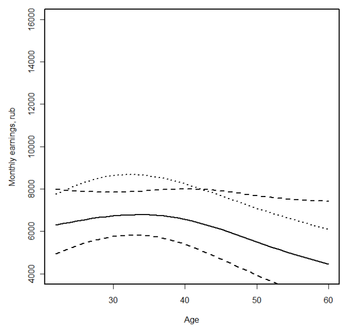
(c) 2b.Lower professionals



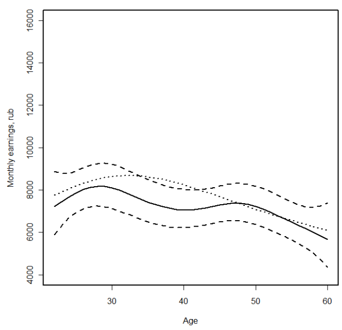
(d) 4/5.Self-employed



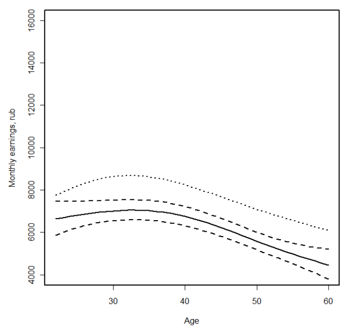
(e) 6.Lower supervisors



(f) 7.Lower sales and service



(g) 8.Lower technical



(h) 9.Routine

Figure 4.12: Class-specific age-earnings profiles, Russia, 2006, men aged 22 to 60, the RLMS. The spline smooths with the 95% confidence intervals. The dotdash line shows the age-earnings profile for all men aged 22 to 60.

classes, there is little variability of earnings across the age groups. Perhaps this is not surprising, given the unstable environment of the Russian labour market, high job mobility and age-based occupational segregation.

However, the profiles for higher and lower professionals and the self-employed are steeper than the profiles for the manual classes for men under 40 (under 30 for lower professionals). This indicates that for these non-manual classes there are some positive returns to work experience, although they are small and limited to younger cohorts. This is not the case for non-manual classes. Although the profiles look different than in Goldthorpe and McKnight's analysis of Great Britain, this indicates that some elements of employment contracts that imply different promotion perspectives for service and manual classes may be at work in Russia, too.

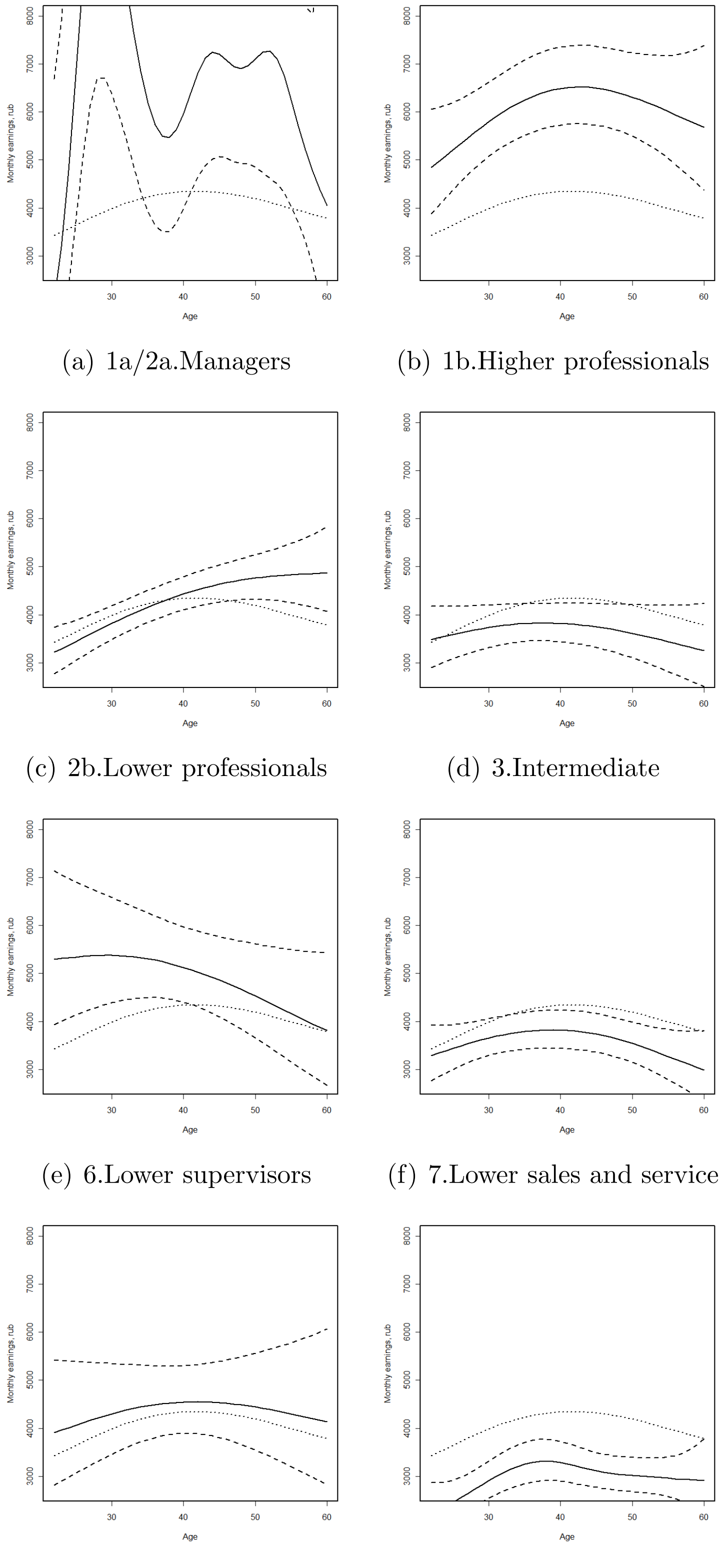
Sixty percent of Russian men are members of the lower technical and routine classes. Only about 20% are managers and professionals (see table 3.1 in chapter 3). Therefore, the shape of the age-earnings profile for men is mostly affected by the patterns observed in manual classes. Had the proportion of non-manual classes been higher, we would probably have observed a steeper profile, with earnings peaking at a later age.

Figure 4.13 shows class-specific age-earnings profiles for women.[14] To avoid overfitting, I use the data for 2005 rather than 2006.

The profile for female managers is similar to that for male managers, with the high average earnings of young women and women aged 40 to 50. Female higher professionals have a symmetric profile, and the average earnings of women aged 40 to 50 are noticeably higher than in the age group 20 to 30.

Female lower professionals (mainly nurses and secondary school teachers) are the only class, in which the earnings of the oldest women are the highest. There is no "decrease" of the age-earnings function at an older age. Perhaps this can

[14] The profile for the self-employed is omitted to keep the figure on one page as the self-employed are the smallest class for women.



(a) 1a/2a.Managers
(b) 1b.Higher professionals
(c) 2b.Lower professionals
(d) 3.Intermediate
(e) 6.Lower supervisors
(f) 7.Lower sales and service
(g) 8.Lower technical
(h) 9.Routine

Figure 4.13: Class-specific age-earnings profiles, Russia, 2006, women aged 22 to 60, the RLMS. The spline smooths with the 95% confidence intervals. The dotdash line shows the age-earnings profile for all women aged 22 to 60.

be explained by the fact that most nurses and school teachers are employed in the state sector of the economy where earnings directly depend on formal rank (*razryad*) and employees are promoted from one rank to another with experience. This is in line with Goldthorpe's class theory. Lower professionals are the largest class for women (about 25% of the female labour force) and the shape of their age-earnings profile strongly affects the age-earnings profile for all women. The unusual, for Russia, shape of the profile for female lower professionals is perhaps the main source of the differences in the shape of the age-earnings profile between men and women.

For the intermediate class (bookkeepers, sales representatives, secretaries) the profile is flat and hardly any association between age and earnings can be found. This is not the case for lower supervisors as the youngest members of this class on average earn more than the oldest. For lower sales and service and lower technical workers the profiles are symmetrical (with earnings "peaking" at age 40), but very little variability in average earnings across the age groups is observed. The profile for routine workers is also almost flat, although the average earnings of women under 30 in this class are somewhat lower than for the older workers.

For women, managers, higher professionals, lower supervisors and lower technical workers have earnings above the average. The earnings of lower professionals under age 40 are close to the average, but are higher than the average after age 40. The earnings in the intermediate class, lower sales and service and routine classes are below the average.

Are class-specific age-earnings profiles in Russia consistent with the British data presented in Goldthorpe and McKnight (2006)? The British profiles for manual classes are almost flat, both for men and women. This is also the case in Russia, although in Russia the earnings of people over 40 are still somewhat lower than the earnings of younger workers. In Britain, there is much more variability in average earnings across the age groups for higher and lower professionals and managers. Older managers and professionals get paid substantially more than their younger colleagues.

The pattern for Russia is more complicated. The profile for Russian managers is very different to the British profile for higher managers and professionals. In fact, the youngest managers in Russia are the most well paid occupational group in the data set. For higher professionals, the profiles in Russia and Britain are more similar, although in Russia there is a smaller difference between the earnings of the youngest professionals and more mature professionals after age 35.

For lower professionals, the shape of the profile for men is highly non-linear and does not correspond to the pattern observed in Britain. For women, however, the profiles for lower professionals in the two countries are similar. This is also the case for women in the intermediate and lower sales and service classes.

In general, although the Russian profiles are much flatter than the British, there is a difference between non-manual and manual classes (both for men and women) and non-manual classes do have greater variability of earnings across the age groups. This can be taken as evidence in support of the validity of Goldthorpe's class theory in Russia.

Before summarizing and discussing the results of this chapter, I present some evidence on the cross-national comparison of age-earnings profiles that illustrates the position of Russia when compared with other countries.

4.9 Cross-national comparison of age-earnings profiles

Figure 4.14 presents a dot plot showing the age of maximum predicted earnings by country for men, drawn from the analysis of the ISSP data for 2006. To keep things simple, I calculate the age of maximum predicted earnings from the parametric regression of earnings on age and age squared by country.[15] The dot plot does not provide any information about the variability of earnings across the age groups, but allows us to compare the age of maximum average earnings in different countries.

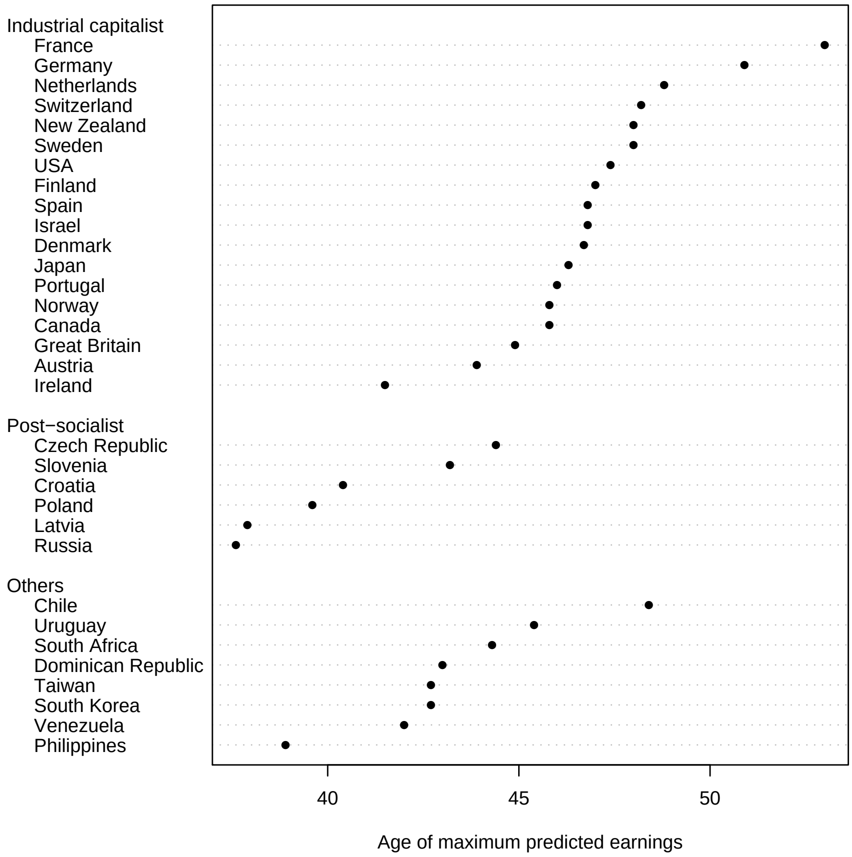


Figure 4.14: Age of maximum predicted earnings by country. ISSP 2006, men aged 18 to 65.

The countries in the plot are divided into three groups: developed capitalist (Western Europe and the USA, Canada, New Zealand, Israel and Japan), post-socialist and others (mainly Asian and South American). In the first group, the age of maximum earnings is over 45 (with the exception of Ireland). In France and Germany, two continental European countries with a strongly regulated labour

[15] $age_{max} = -b_{age}/(2 * b_{age^2})$

market, the age of maximum earnings is over 50.

The age of maximum earnings in post-socialist countries is noticeably lower. Russia is an extreme case, with the age of maximum earnings lower than in any other country in the ISSP. Latvia, another former USSR republic, is similar to Russia. Poland has the next lowest age in the group of post-socialist countries. In the group of Asian and South American countries, the average age of maximum earnings is somewhere in between Western industrial and post-socialist states.

In the light of the previously discussed hypotheses, two explanations can be given for these findings. First, the proportion of manual classes in the labour force is higher in Eastern Europe than in Western Europe. It can be suggested that the earnings of manual workers do not rise with age (according to Goldthorpe's theory) and, in fact, peak earlier as younger workers in these occupations can be more productive. Therefore, the age of maximum predicted earnings in the countries with a larger share of manual workers should be lower.

However, these cannot explain the difference between, on the one hand, Eastern European and, on the other hand, Asian and South American countries. Another possible explanation is that the age of maximum earnings in post-socialist countries declined as a result of the structural economic reforms and the age segregation in the labour market. This hypothesis can be tested quantitatively; however, this is beyond the aims of this chapter.

4.10 Discussion

In contrast to Western societies, Russian age-earnings profiles show that there is very little variability in average earnings across the age groups. Work experience does not pay in Russia, and older workers, especially men, are paid less than their younger colleagues. For most of the years studied, the age of maximum predicted earnings is about 30 to 35 for men and 40 to 45 for women. In this chapter I suggested several hypotheses that can explain this pattern and tested them against available evidence.

The explanation of the shape of age-earnings profiles that is most popular in the economic literature is related to the human capital function. According to this theory, Russian age-earnings profiles can be explained by a mismatch in the human capital of older workers. The human capital of older cohorts who were educated and acquired their labour market experience in Soviet times could not be applied in the conditions of the post-Soviet market economy. This can potentially explain low returns to work experience and the comparative advantage of younger cohorts.

However, the evidence presented does not support this hypothesis. First, the Russian age-earnings profiles in 1991, before the beginning of the structural economic reforms, were already different to the British and American profiles.[16] Therefore, even if there was a mismatch in human capital, it could only be part of the explanation. Second, this does not explain the difference in the shape of the profiles between men and women (for women, earnings "peak" later). If there was a mismatch, it should have had an equal effect on men and women. Third, the human capital hypothesis only applies to certain occupations. It is hard to imagine that the content of work changed so much for manual workers during the economic transition that their previous work experience was no longer relevant. However, the examination of class-specific age-earnings profiles showed that even if the profiles for manual classes are flatter than for non-manuals, older workers in these classes still earn less than younger workers. The age of maximum predicted earnings in manual classes is actually lower than in non-manual classes.

As already discussed in section 4.3, the theory of delayed payment contracts and the effect of the cohort size on earnings cannot help us explain the shape of Russian age-earnings profiles either. The theory of delayed payment contracts contradicts the evidence about high job mobility in Russia. The effect of the

[16] It is more correct to compare the 1991 profiles for the USSR with Western profiles at the same point of time. Murphy and Welch (1990) present the average experience-earnings profile for the USA in the period 1963 to 1986. It looks similar to the profile based on the 2006 CPS data, shown in the beginning of this chapter.

cohort size is unlikely to be large and, besides, it should be positive for the oldest rather than the youngest cohorts.

The difference in health between older and younger workers is a more plausible explanation. This can also potentially explain the difference in the shape of the profiles between men and women, as older women in Russia are healthier than older men. However, health does not automatically affect earnings, but does this through several labour market mechanisms. First, unhealthy people drop out of the labour force (and, therefore, they are excluded from age-earnings profiles and cannot affect their shape). Second, less healthy people can be less productive, and can be paid less even if employed in the same jobs as healthier people. This hypothesis requires a separate test. Third, less healthy people can be selected into less physically and psychologically demanding occupations and jobs with lower pay. But if this is the case, then the effect of health on the association between age and earnings is mediated by the mechanism of age segregation in the labour market.

In section 4.3 I discussed how structural economic reforms can lead to the emergence of age segregation in the labour market. Available evidence suggests that Russian workers of different ages were indeed unevenly distributed across the sectors of the economy. There was a higher proportion of older workers in the sectors with lower pay. Although the RLMS does not have the sample size that allows us to test the hypothesis about age segregation at the occupational level, it is reasonable to suggest that the average age in occupations with higher pay was lower. Qualitative evidence collected by Clarke (1999) confirms that more successful firms gave preference in the hiring policy to men under 35.

The dynamics of age segregation in the labour market can explain the change in the shape of age-earnings profiles for men in the middle of the 1990s (when the profiles for men under age 45 were flat). This was a period when traditional enterprises in the old sector of the economy experienced a deep economic crisis while more successful firms in the new private sector emerged. When entering the labour market younger workers tended to avoid depressed enterprises and, if already employed, were more likely to change jobs and move to firms with better pay. Sabirianova (2002) showed that job mobility in the middle of the 1990s was at its peak.

However, the emergence of age segregation in the labour market during the structural economic reforms is unable to explain why the shape of the profile in 1991 was already different to what is observed in Britain and the USA. A possible explanation is the difference in the class composition of Russia and Western industrial countries. There is a higher proportion of manual classes in Russia, especially for men. Following Goldthorpe and McKnight (2006), I showed that the shapes of age-earnings profiles in Russia vary across the occupational classes. For manual classes the profiles are flatter, and the age of maximum predicted earnings is lower. Hence the proportion of manual workers among men is high, this affects the shape of the profile for all men. For women, the largest class in Russia is lower professionals, for whom the oldest workers earn more than their younger colleagues, so that the profile monotonically increases. This explains why the shape of the profile for women is different to men, and average earnings "peak" later.

The analysis of the class-specific age-earnings profiles also demonstrates that despite some peculiar characteristics of the Russian labour market and low returns to work experience, the logic of Goldthorpe and McKnight (2006) can be applied to Russia as well as to Britain.

It should be noted that it is unlikely that any of the suggested factors is the only explanation of the shape of age-earnings profiles observed in Russia. All these factors may well jointly affect the association between age and earnings. While labour economists usually focus on human capital when they explain age-earnings profiles, this work suggests that it is also important to take into account occupational characteristics, including class.

The results presented above can be discussed in terms of age, period and cohort effects. I do not try to separate these effects statistically, because the available data do not cover the period that is long enough for this type of analysis. Nevertheless, the effects can be discussed informally and some conclusions can be made. Period effects on earnings are perhaps the easiest to separate. Real earnings in Russia fell dramatically after the collapse of the USSR, then slightly recovered in 1996 and 1997, fell again after the financial crisis of 1998 and rose from 1999 to the crisis of 2008. This dynamic was driven by the macroeconomic conditions in the country.

Age and cohort effects are more difficult to separate. The argument about the effect of age segregation in the labour market implies that the changes in the shape of age-earning profiles were brought about by cohort-specific behaviour. The younger cohorts of men had higher chances of job mobility and were more likely to be employed in successful enterprises, while older cohorts got stuck in depressed sectors of the economy. If this was the only reason for the unusual shape of age-earnings profiles for men, then as time passes the profiles should take on the shape that is characteristic for Western countries. New cohorts entering the labour market will not have the earnings advantage that was experienced by the younger cohorts during the economic transition. It is also reasonable to suggest that returns to work experience in the Russian labour market will be rising with economic stabilization.

On the other hand, if class composition is the main factor that affects the shape of age-earnings profiles, it can be suggested that the present shape will remain in future cohorts (unless the class composition in Russia changes). In this case, the effect should be discussed in terms of age rather than cohorts. Time will show if the advantage in average earnings of younger men over older men in Russia will persist.

Chapter 5

Class Inequality in Mortality in Russia

5.1 Social class and inequality in mortality: A review

In the previous two chapters I demonstrated the relevance of occupational social class for the analysis of labour market outcomes in post-Soviet Russia. To further analyze how social inequality in Russia is shaped by class, I turn now to the analysis of the class gap in mortality.

In the last fifty years social inequality in health and mortality has been an important topic in public health, sociology and economics (see Elo (2009) for a recent review). Whether measured by education, income, socio-economic status or occupational class, inequalities in longevity and mortality were found in all countries where the data are available.

In many studies different measures of social inequality were used interchangeably and differences between educational, income and occupational health inequalities were not conceptualized. In the public health literature, researchers often use socio-economic status (SES) as the indicator of an individual's position in the social hierarchy. SES can be operationalized in many different ways, usually as some combination of education, income, occupation or other, related characteristics measured either at the individual or aggregate level. Recently students of health inequality recognized that these inequality measures may not reflect the same latent dimension of inequality and can in fact be associated with health and mortality via different causal mechanisms (Duncan et al., 2002; Geyer et al., 2006; Torssander and Erikson, 2010; Goldthorpe, 2010).

In the literature several causal mechanisms were suggested that relate the social standing of individuals with their health. Education can affect health via the knowledge and adoption of healthy behaviour and lifestyles. Another possible mechanism for the effect of education is psychosocial attitudes and the ability to cope with stress (Elo, 2009). Income may affect access to medical and recreational facilities. Occupation, net income and education, can be related to health via the exposure to dangerous and unhealthy work conditions. Status anxiety is another mechanism that can explain the association between social standing and health (Wilkinson, 1996). People with lower social standing (whether defined by class, income, education or other measures) experience more stress because of their subordinate position.

Income is often used as a measure of social inequality in mortality, but reverse causation emerges as a problem with this research design. Many studies showed that income is inversely associated with mortality risks, but the interpretation of this association is debatable. In sociology and public health, researchers often interpret it as evidence of the causal effect of income on health. In economics the prevalent view is that in this case reverse causation is more important. Bad health drives people out of the labour market, forces them to work part-time and reduces their earnings (Cutler et al., 2006). It is hardly possible to resolve this debate without using detailed life course data.

If education is chosen as a measure of social inequality, the problem of reverse causation becomes smaller, as people usually finish their education in early adulthood. This excludes the possibility of health affecting their education in later life. However, there are other disadvantages of measuring social inequality in health with educational categories. First, due to the educational expansion in the second half of the 20th century, the educational distributions across birth cohorts differ, which makes people of different generations harder to compare. Second, some educational groups (for instance, people with university degrees) are quite heterogeneous in terms of their labour market position.

Social class has been routinely used in the studies of health inequality in Europe and in particular in Britain, although in the USA researchers mostly focused on education and income rather than class. Data on the differentials in mortality by occupation have been published in Britain since the census of 1851. In 1921-23 the concept of occupational social class was for the first time used for the analysis of mortality (Pamuk, 1985). The advantage of using class for the study of health inequality is that it provides a clear description of the distribution of inequality across occupational groups and may reveal specific health risks associated with occupation rather than education. The disadvantage is that detailed occupational data are not always available in large data sets suitable for studying mortality, especially outside Western Europe and North America.

My goal in this chapter is to provide a detailed description of occupational class inequality in mortality in Russia rather than to disentangle the causal effects of occupation, income and education or to test the specific causal mechanisms through which class affects health, net of other factors. The identification of causal effects is a specific task in statistics that usually requires a special research design and rarely can be achieved by simply entering several socio-economic measures in regression equations simultaneously (see chapter 2 for a detailed discussion). Identifying the causal effects of fundamental variables, such as class, is particularly difficult. To date, most of the class analysis in sociology and public health has been descriptive. In this chapter I follow this tradition.

In the last fifteen years, several researchers compared the class differentials in mortality in European countries. Kunst et al. (1998) analyzed male mortality by class in eleven European countries with data from the 1980s. They found that the manual to non-manual mortality rate ratios were similar in most countries, apart from France and to a lesser extent Finland where the ratios were higher. Somewhat surprisingly, health inequality in Nordic countries where social policies are more egalitarian, was not lower. For France, Kunst et al. (1998) suggested that high class inequality in mortality could probably be explained by the class differences in alcohol consumption.

More recently, Mackenbach et al. (2008) analyzed newer data on the educational and occupational inequalities in mortality in 22 European countries. They found that in Eastern European and the post-Soviet Baltic countries educational inequality in mortality was much larger compared to Western Europe, while, on the other hand, the inequalities in Southern European countries (Italy and Spain) were smaller. Data on occupational inequalities were available only for a limited number of countries. As in the earlier study by Kunst et al., class inequalities in mortality appeared to be higher in France and Finland. No evidence was found in support of the hypothesis about smaller inequalities in Nordic European countries.

5.2 Inequality in mortality in post-Soviet Russia

After the collapse of the USSR mortality in Russia dramatically increased and life expectancy fell. In 1990, men's life expectancy at birth in Russia was 63.8 years, and by 1994 it had decreased to 57.6 years. Women's life expectancy at birth in the same period decreased from 74.4 to 71 years (Leon et al., 1997). Figure 5.1 illustrates the dynamics of crude mortality rates in Russia in the post-Soviet period using the official data of the Russian Statistical Office (Rosstat, 1996-2009a).

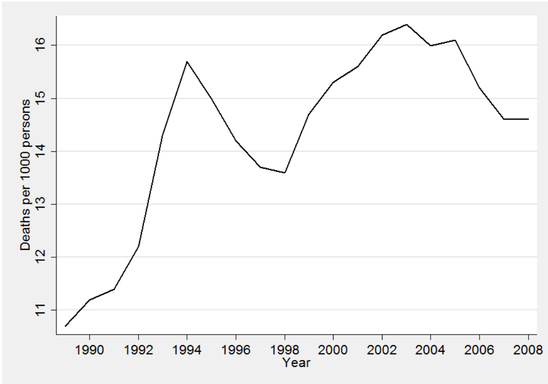


Figure 5.1: Crude mortality rate per 1000 persons, Russia 1989-2008. Source: the Russian Statistical Office.

Several explanations were suggested for the rise of mortality in Russia in the post-Soviet period. They include mass impoverishment and malnutrition, the deterioration of the health system, psychological stress from the rapid social and economic change, the increase of alcohol consumption, mass privatization and unemployment (Shkolnikov et al., 1998a; Stuckler et al., 2009). In many studies, alcohol was considered to be the most important immediate mechanism of the mortality crisis in Russia (Leon et al., 1997; Walberg et al., 1998; Brainerd and Cutler, 2005; Tomkins et al., 2007; Leon et al., 2007, 2009).

The mortality crisis affected different groups of the population in different ways. Men suffered more than women, although female mortality rates grew as well. Somewhat surprisingly, the mortality rates in the middle-aged population increased more than among the youngest and the oldest people (Shkolnikov et al., 1998a). Several studies looked at the educational differentials in mortality rates in the USSR and their change in the post-Soviet period. In 1979, life expectancy between ages 20 and 69 (e(20-69)) was four years higher for men with higher education compared to men with incomplete secondary education (and about 1.5 years higher for women). In 1989, the gap in e(20-69) increased to 6 and 2.5 years, respectively. By 1994, the educational gap in mortality further widened by 15-20% (Shkolnikov et al., 1998b). Using the data from a prospective cohort study conducted in St.Petersburg, Plavinski et al. (2003) found that mortality among male university graduates did not increase in the 1990s compared to the 1980s, while mortality among men with incomplete secondary education increased by about 75%.

Several interpretations can be suggested for the widening mortality gap between the educational groups in post-Soviet Russia. The economic and social crisis of the 1990s could affect the least educated people more strongly than the others. On the other hand, the widening educational gap in mortality can be possibly explained by the fact that the educational structure of the Russian population has been changing across birth cohorts. While in the oldest cohorts most people have secondary or incomplete secondary education, in the recent cohorts many more people acquired higher education. In the oldest cohorts incomplete secondary education was the most widely spread educational level, but in the recent cohorts it was characteristic only for the most disadvantaged groups of population. Thus, it is hard to compare people with the same level of education across the birth cohorts.

Recently, a number of studies analyzed the socio-economic determinants of Russian mortality with the panel data from the RLMS. Brainerd and Cutler (2005) looked at the statistical association between mortality hazards and income per capita. Income was found to be related to mortality, although the effect was statistically significant only at the 10% level and in fact it was not statistically significant in some model specifications. Perlman and Bobak (2008) established that education, but not income and material resources, strongly predicted mortality. In their later study, Perlman and Bobak (2009) analyzed mortality in the working age population and found that male unemployment increased mortality hazards, as well as payment in consumer goods among men and compulsory unpaid leave among women. Denisova (2010) found similar effects for unemployment and education. Although income was not statistically significantly associated with mortality, the experience of being under the poverty line increased mortality hazards. The experience of self-employment and labour market mobility lowered the mortality hazards. Denisova also included three perceived status variables (perceived wealth, perceived power and perceived respect measured on nine-point scales) as predictors of dying. Perceived respect was found to be associated with mortality, even after controlling for a number of covariates. Billingsley (2009) found a negative effect of male downward mobility (defined as a change of rank on the perceived wealth scale) on survival.

None of these studies analyzed differences in mortality by occupational class. My goal in this chapter is to fill this gap in the literature. For the first time in the literature, I estimate the class gap in mortality in post-Soviet Russia, both in a crude form and adjusted for some covariates. I also estimate the associations between mortality and class mobility, working in the public sector and perceived social standing. Then I compare class mortality rates and ratios in Russia with the results previously estimated for other European countries.

The chapter proceeds as follows. In section 5.3 I describe the data and measures of mortality, class and other variables. Section 5.4 introduces the statistical techniques that I use in further analysis. Sections 5.5 to 5.8 present the results. First, in section 5.5 I estimate crude and standardized class-specific mortality rates and ratios. Section 5.6 presents Kaplan-Meier survival curves and class-specific life expectancies. Section 5.7 presents the results from Cox proportional hazards analysis. Section 5.8 compares the class gap in mortality in Russia with England and Wales and other European countries. Section 5.9 summarizes the results and discusses them in the context of the risk factors related to the market transition in Russia.

5.3 Data and measures

The data on Russian mortality come from the RLMS, 1994-2006. The RLMS is a household panel survey, and the data on the household roster are collected in each round (see details in chapter 1). If a person who used to be a member of the household is missing, the information about the reasons for his/her absence (including death) is collected from other members of the household and recorded. After reshaping and merging the household roster and individual data sets in the RLMS, it becomes possible to link dead individuals with their individual questionnaires from the previous rounds.

The RLMS was previously used as a source of data on Russian mortality in a number of studies reviewed above (Brainerd and Cutler, 2005; Perlman and Bobak, 2008, 2009; Denisova, 2010; Billingsley, 2009). Perlman and Bobak (2008) report the mortality rates in the RLMS that are very close to the official estimates made by the Russian Statistical Office on the basis of death records. Among people aged over 18, the SMRs (the standardized mortality ratios that compare the official mortality rates with the estimates from the RLMS) were reported as 0.96 for men and 0.78 for women. In other words, the RLMS mortality rates were found only 4% lower than official for men and 22% lower for women.

Perlman and Bobak (2008) exclude from their analysis people who come from single-person households (as in this case nobody can report their death) and, more importantly, people whose household identification numbers do not match across the RLMS rounds. This methodological decision has its caveats. The RLMS tried to follow people who were changing households within the same primary sampling unit. If these people were found at a new address or formed a new household at the old address (for instance, married children splitting from the parents' household, but continuing living at the same address), they were assigned a new household id. Therefore, excluding people whose identification numbers do not match across the RLMS rounds leads to excluding all the "movers". The "movers" tend to be younger than average in the sample and the mortality rates among them are lower. Therefore, the decision to exclude the "movers" biases the sample and artificially increases real mortality rates in the RLMS.

Contrary to Perlman and Bobak (2008), I keep in the sample all respondents and do not exclude the "movers". In the follow-up period, 1,557 deaths were identified in 147,115 person-years (21,275 people, mean follow-up 6.9 years). For the analysis that I undertake, this is not a very large sample. However, this is the best data that are available at the moment for the evaluation of the inequality in mortality in Russia.

According to my estimates, the mortality rates in the RLMS are 17% lower than the official national rates (averaged for 1994-2006) for men and 39% lower for women. These estimates are lower than those previously reported by Perlman and Bobak (2008), which is the result of keeping the "movers" in the sample. Lower mortality rates in the RLMS are hardly a surprise, as the survey does not include the institutionalized population (people in the army, prisons, hospitals, etc.) and homeless people. Besides, the most disadvantaged people with poor health are likely to have a higher non-response rate.

The difference between the official and the RLMS mortality rates is higher for women than for men. Most of the difference comes from the underestimation of mortality among elderly women. As Russian men tend to die relatively young, older Russian women frequently live alone and, therefore, their deaths are under-reported in the RLMS. This is illustrated in Figure 5.2 that shows age-specific mortality rates for men and women in the RLMS compared to the official national estimates.

As in the previous chapters, I use the European Socio-Economic Classification (ESeC) (Rose and Harrison, 2010) to code class. Managers were separated from higher and lower professionals, and the self-employed and self-employed farmers were combined into the same class.

In longitudinal data, class can be coded as a time-constant or time-varying variable. For most of the analysis in this chapter, I code class as time-constant on the basis of occupation, employment and supervisory status of respondents in the

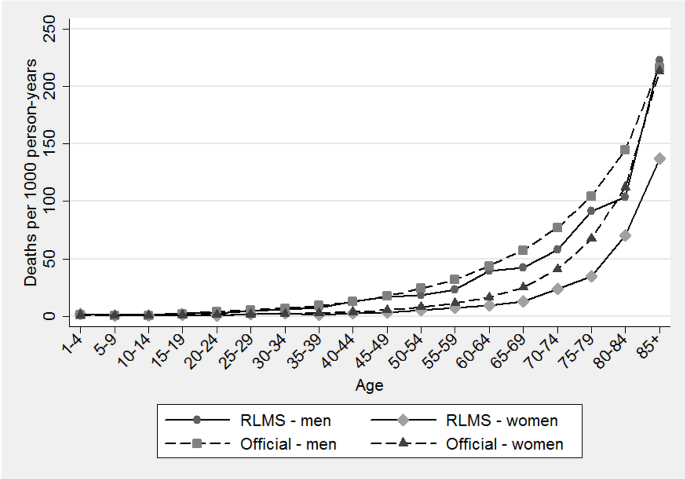


Figure 5.2: Age-specific mortality rates in the RLMS compared to official rates, 1994-2006. Sources: Russian Statistical Office, author's calculations from the RLMS.

RLMS round when they were first observed. If the information on occupation in that round is missing, I use the data from the next round, and so on. For people whose class cannot be coded with their present occupation, I use retrospective information on occupation in 1990 and if that is missing as well, in 1985.

For most respondents in the sample, class was coded at the beginning of the Russian market transition, as the RLMS panel started in 1994. Coding class as time-constant allows us to estimate the differences in mortality between classes as they were in the beginning of the market transition, without taking into account class mobility during the post-Soviet period. Instead, in section 5.7, I model the mobility directly. In the same section, I also present models with time-varying rather than time-constant class. The results for both operationalizations of class are consistent with each other.

The analytic sample was limited to people aged 21 to 70 years. Including older people would introduce a bias, as class can be coded only for those of them who kept working for a long time (even if retrospective information is used).

Class was treated as an individual rather than a household characteristic. It was coded only for people who were in the labour force at some point of the observation or provided retrospective data on their occupation. Using this procedure, I coded class for 88% of men (5,939 out of 6,742) and 83% of women (6,382 out of 7,675) in the analytic sample. Missing groups included people who were not employed at any point of the study (long-term unemployed, sick, housewives, students).

The analytic sample included 617 deaths of men (6,742 persons, 41,951 person-years) and 216 deaths of women (7,675 persons, 49,420 person-years). The number of deaths for women is smaller than for men as women in Russia on average live much longer than men (and, therefore, many female deaths were not included in the analytic sample as this was limited to people under 70 years). As will be clear from the following analysis, the confidence intervals for women are larger and the estimates are less reliable.

As the patterns of mortality are likely to be different for men and women, all the analyses were stratified by sex.

In some analyses, I compare mortality in manual vs. non-manual classes. Managers, higher and lower professionals, intermediate workers and the self-employed were coded as non-manual classes. Lower supervisors and technicians, lower sales and service, lower technical and routine workers were coded as manual classes.

For the analysis in section 5.7, upward class mobility was coded as a dummy variable for moving from a manual class to a non-manual class during the follow-up period. Downward mobility was defined as a dummy variable for moving from a non-manual to a manual class.

In the RLMS, respondents were asked the following questions: 1) "And now, please imagine a nine-step ladder where on the bottom, the first step, stand the poorest people, and on the highest step, the ninth, stand the rich. On which step of the nine steps are you personally standing today?", 2) "And now, please imagine a nine-step ladder where on the bottom, the first step, stand people who are completely without rights, and on the highest step, the ninth, stand those who have a lot of power. On which of the nine steps are you personally standing today?", 3) "And now another nine-step ladder where on the lowest step stand people who are absolutely not respected, and on the highest step stand those who are very respected. On which of the nine steps are you personally standing today?". These scales were used for coding perceived wealth, power and respect. The scales were reversed so that one was coded as the highest rank and nine as the lowest rank.

As in the two previous chapters, the public sector of the economy was defined as enterprises that are 100% state-owned. This variable was coded as time-constant with the information on the same job that was used for coding time-constant class.

5.4 Methods

For the analysis of mortality I used several statistical techniques that are frequently applied in epidemiology.

First, I calculated crude (not standardized by age) class mortality rates. The confidence intervals for the rates were calculated with the quadratic approximation to the Poisson log-likelihood for the log-rate parameter, as implemented in Stata's command `strate` (Stata, 2007).

In epidemiology, there are two methods to standardize mortality rates by age, the direct and the indirect standardization. The direct method calculates the weighted averages of age-specific mortality rates for each class, and the age distributions in classes are used as weights. This method requires estimating mortality rates in every age band (usually five-year) for each class. It is often used in official statistics, but is not appropriate when the sample is relatively small, as is the case with the RLMS.

To produce standardized mortality estimates for each class, I used indirect standardization. Indirect standardization compares the observed number of deaths in each class with the number of deaths that would be expected if we applied the average age-specific mortality rates in the population, and calculates the standardized mortality ratios (SMRs) (Bruce et al., 2008). For example, if the SMR for a given class equals one, this means that the mortality rate for this class is the same as average in the sample, conditional on the age composition of this class. If the SMR equals 1.5, this means that for each 10 deaths that would be expected given the age composition of this class and age-specific mortality rates in the population, there are 15 observed deaths, so the age-standardized mortality rates in this class are 1.5 times higher than on average in the sample. For presentational purposes, I multiplied SMRs by 100. Formally,

$$SMR = 100 * \frac{\sum d_k}{\sum R_k n_k} \tag{5.1}$$

where $\sum d_k$ is the observed number of deaths in a given class (the sum of deaths across k age bands), R_k are the age-specific mortality rates in the whole population and n_k is the number of people in the age band k in a given class.

In the next stage of the analysis I estimated the nonparametric Kaplan-Meier survival functions for each class. The Kaplan-Meier estimator gives the proportion of people survived in each age, taking into account right censoring (the fact that most people leave the study before dying). The Kaplan-Meier estimator is given by:

$$S(t) = \prod_{t_i \leq t} (\frac{n_i - d_i}{n_i}) \tag{5.2}$$

where t_i is age (if age is set as the analytic time variable), n_i is the number of people at risk at age i and d_i is the number of censored events at age i.

Using the survivor functions produced with the Kaplan-Meier method, it is easy to estimate life expectancies for each class. The life expectancy at age i is the sum of proportions of people survived at each age from i to the last age observed.

$$e(i) = \sum_{t=i}^{max} S(t) \tag{5.3}$$

It is also possible to estimate life expectancy between ages i and j.

$$e(i-j) = \sum_{t=i}^{j} S(t) \tag{5.4}$$

It can be interpreted as the number of years that an average person in a given class lives between ages i and j.

Finally, I fitted Cox proportional hazards models. These are multivariate regression models for survival data. Contrary to standard OLS regression, Cox models take into account right censoring and allow us to include in the model time-varying predictors.

$$h_i(t) = h_0(t)e^{\boldsymbol{\beta x_i}}, \tag{5.5}$$

where $h_i(t)$ is the hazard for individual i at time t, $h_0(t)$ is the baseline hazard function and $\boldsymbol{\beta x_i}$ is the vector of predictors for i multiplied by the vector of coefficients. t is the analytic time (in this chapter I always use age as the analytic time variable). The model is semi-parametric as it does not rely on any particular functional form for $h_0(t)$ and estimates it from the data. It also assumes the proportionality of hazards. In other words, the hazards ratio (HR) for any two individuals i and j does not depend on the analytic time t and remains the same in all ages (if age is set as the analytic time). See Cleves et al. (2008) for details.

In section 5.8 I compare the manual to non-manual mortality rate ratios in Russia and several European countries. The mortality rate ratio (RR) is simply a ratio of the mortality rates for manual vs. non-manual classes.

$$RR = \frac{MR_{manual}}{MR_{non-manual}} \tag{5.6}$$

The 95% confidence intervals for the rate ratios were calculated with the Mantel-Haenszel-type method, as implemented in Stata's command `stmh`.

Kunst et al. (1998) proposed a method for the adjustment of mortality rate ratios in order to account for the exclusion of people for whom class was not coded (i.e., economically inactive people). As these people are more likely to come from disadvantaged classes, excluding them underestimates class inequality in mortality. To correct for this, Kunst et al. (1998) assumed that the members of manual classes were twice more likely than the members of non-manual classes to be economically inactive (this assumption was based on the survey data). Then the adjustment factor for the manual to non-manual rate ratio is given by:

$$AF = \frac{1 + 1.4P * (RR - 1)}{1 + 0.7P * (RR - 1)} \tag{5.7}$$

where P is the proportion of the economically inactive population (those for whom class was not coded) in the total number of person-years and RR is the mortality rate ratio of the economically active to the economically inactive population.

To calculate the adjusted manual to non-manual rate ratios, we need to multiply them by the adjustment factor. In the RLMS data, for men aged 30-64 in Russia the adjustment factor equals 1.08.

5.5 Class-specific mortality rates

Table 5.1 presents crude mortality rates and age-standardized mortality ratios for ESeC classes, separately for men and women.

The male mortality rates and SMRs for the non-manual classes are noticeably lower than for the manual classes. Within the non-manual classes the SMRs are not statistically significantly different. The SMRs of higher and lower professionals are very similar, and these classes are followed by managers, the self-employed and

Table 5.1: Class Inequality in Russian Mortality. Crude and Age-Standardized Mortality Rates, by Sex, 1994-2006 (people aged 21-70 years old)[a]

European Socio-Economic Classification	Men			Women		
	Number of deaths	Crude Mortality Rate per 1000 person-years (95% CI)	Age-Standardized Mortality Ratio (95% CI)	Number of deaths	Crude Mortality Rate per 1000 person-years (95% CI)	Age-Standardized Mortality Ratio (95% CI)
1a/2a.Managers	12	10.9 (6.2 to 19.2)	56 (32 to 99)	5	4.6 (1.9 to 11.1)	92 (38 to 221)
1b.Higher professionals	25	8.5 (5.8 to 12.6)	48 (33 to 71)	13	2.6 (1.5 to 4.4)	58 (33 to 99)
2b.Lower professionals	26	7.7 (5.2 to 11.3)	53 (36 to 78)	15	1.6 (1.0 to 2.6)	44 (26 to 72)
3.Intermediate	5	6.3 (2.6 to 15.0)	61 (25 to 146)	12	2.6 (1.5 to 4.6)	75 (42 to 132)
4/5.Self-employed	16	6.6 (4.0 to 10.8)	63 (39 to 103)	3	2.0 (0.6 to 6.1)	69 (22 to 213)
6.Lower supervisors	44	15.4 (11.5 to 20.7)	108 (81 to 145)	4	1.7 (0.6 to 4.4)	44 (17 to 117)
7.Lower sales and service	18	12.9 (8.1 to 20.5)	140 (88 to 223)	24	3.4 (2.3 to 5.1)	88 (59 to 131)
8.Lower technical	157	15.4 (13.1 to 18.0)	99 (85 to 116)	17	6.7 (4.2 to 10.8)	160 (99 to 257)
9.Routine	201	13.1 (11.4 to 15.0)	88 (77 to 101)	55	4.5 (3.5 to 5.9)	85 (65 to 110)
Not in the labour force	138	43.0 (36.4 to 50.8)	296 (251 to 350)	75	14.5 (11.6 to 18.2)	266 (121 to 334)

[a] Crude mortality rates were standardized using the indirect method. The RLMS sample was taken as the standard population having an SMR of 100.

the intermediate class. In the manual classes, the differences between classes do not reach the conventional level of statistical significance either, but note the lower SMR of routine workers compared to lower technical (i.e., skilled manual) workers and manual supervisors. The male lower sales and service workers have the highest mortality rates, but the estimates for them are less reliable due to the small number of deaths in this group.

Note that the SMR of men who are not in the labour force (and hence could not be assigned any class) are particularly high. The age-adjusted mortality rates of these people are about three times higher than on average in the population. In this case, the direction of causality is particularly likely to be reversed. Most likely, these people are not in the labour force partly for the reason of bad health. Descriptively, however, this is the most vulnerable group in the Russian population.

For women, the differences in the SMRs between classes are less clear, although non-manual classes do tend to have lower SMRs compared to manual classes. If we exclude from the analysis the three classes with less than ten deaths, lower professionals have the lowest SMR, followed by higher professionals and intermediate workers. Routine and lower sales and service workers have higher SMRs, and lower technical workers have the highest SMR.

Note that for women, as well as for men, routine workers have a lower SMR than lower technical workers. Also, somewhat surprisingly, female lower professionals have a lower SMR than higher professionals.

Admittedly, the confidence intervals for the mortality rates and SMRs are large, especially for women. Some of the class differences could result purely from chance. This is an inevitable effect of the limited statistical power of the RLMS sample. The number of observations for some classes is particularly small and this leads to the large standard errors for the rates. In particular, the SMRs for the classes with less than ten deaths should be taken with caution. For men, this is the intermediate class and for women these are managers, the self-employed and lower supervisors and technicians.

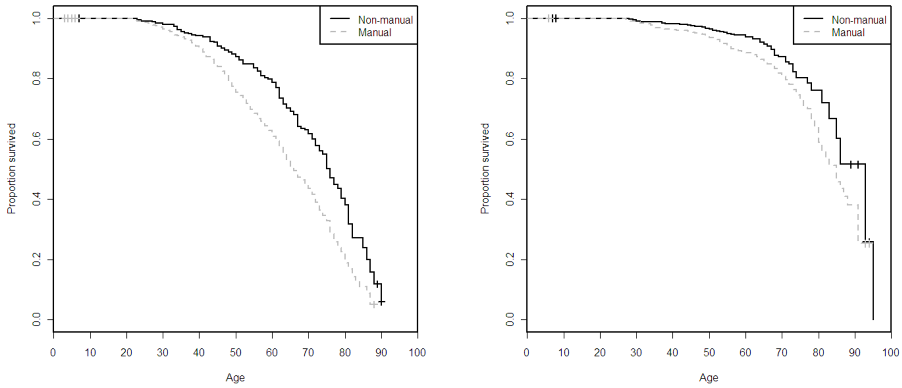
The differences between some, but not all classes reach statistical significance at the conventional 95% level. However, the lack of 95% significance should not be misinterpreted. It does not mean that the true difference in the population equals zero, but rather that the difference between the classes would be achieved in fewer than 95 of each 100 random samples the size of the RLMS. The lack of statistical significance at the conventional level should not be interpreted as evidence of the equality of class-specific mortality rates. If the sample was larger, some of the insignificant differences would have become significant. In any case, the presented rates are the best estimates that can be made with the available data.

5.6 Kaplan-Meier survival curves and class-specific life expectancies

In the next stage of the analysis I estimated Kaplan-Meier survival curves and calculated class-specific life expectancies. Figure 5.3 presents the Kaplan-Meier curves for men and women. For presentational purposes, I combined classes into two groups: non-manual and manual, as defined in section 5.3. It is visually clear both for men and women that the non-manual classes have higher proportions of survival than the manual classes. For women the manual/non-manual gap is smaller than for men.

Using the survivor functions produced with the Kaplan-Meier method, I estimated the class-specific life expectancies at age 15 and between ages 20 and 69. They are shown in Table 5.2.

As the mortality rates in the RLMS are lower than in the official statistics, the life expectancies are higher than those estimated by the Russian Statistical Office. The difference between the official life expectancies at age 15 (e15) and



(a) Men (b) Women

Figure 5.3: Kaplan-Meier survival curves, by class and gender. The non-manual classes include managers, professionals, the intermediate class, the self-employed. The manual classes include lower supervisors, lower sales and service, lower technical and routine workers.

Table 5.2: Life expectancies at age 15 and between ages 20 and 69

	Men		Women	
ESeC	e15	e(20-69)	e15	e(20-69)
1a/2a.Managers	58.6	46.1	62.6	48.4
1b.Higher professionals	56.9	45.0	65.9	48.6
2b.Lower professionals	57.3	43.8	70.3	48.4
3.Intermediate	53.0	42.1	66.4	47.8
4/5.Self-employed	50.7	43.4	55.9	48.2
6.Lower supervisors	47.7	40.3	64.1	48.8
7.Lower sales and services	43.0	35.0	66.8	47.3
8.Lower technical	48.2	39.2	58.3	47.0
9.Routine	50.6	40.8	65.7	46.9
Class could not be coded	33.1	27.6	49.9	38.7
All[a]	48.3	39.1	63.4	46.3
Official (1994-2006)[b]	45.8		58.7	

[a] Including people for whom class could not be coded.
[b] The average official estimates by the Russian Statistical Office for 1994-2006.

the life expectancies estimated from the RLMS is 2.5 years for men and 4.7 years for women, i.e. the RLMS estimates are 5% and 7% higher, respectively.

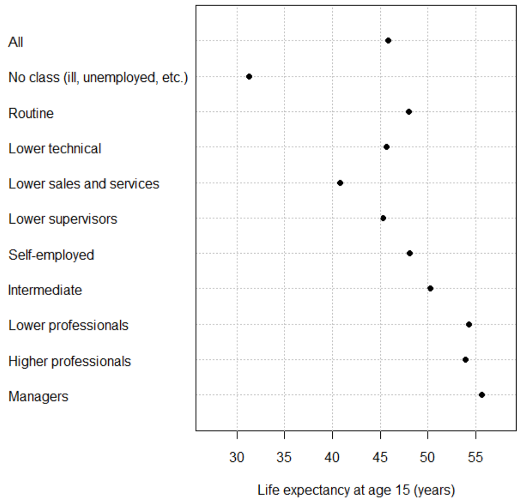


Figure 5.4: Life expectancy at age 15 by class, men. Adjusted for the differences between the RLMS and official mortality rates.

With the limited sample size, e15 may not be very reliable as it depends on the distributions of a small number of people in an old age. Therefore, I also estimate life expectancies between ages 20 and 69 (e(20-69)). They can be interpreted as the number of years that an average member of a given class aged 20 may expect to live between ages 20 and 69 if the mortality rates in all subsequent ages remain the same. The maximum value for e(20-69) is 49 years $(69 - 20 = 49)$. This statistics does not take into account the class differences in mortality for people aged over 69.

As life expectancies directly depend on age-specific mortality rates, it is not surprising that class life expectancies follow the same pattern as the SMRs. However, life expectancies allow us to interpret the results in a more straightforward way. As follows from Table 5.2, male higher professionals at age 15 are expected to live about nine years longer than lower technical workers and about six years longer than routine workers.

We can also adjust the life expectancies for the differences between the RLMS and official mortality rates, simply by reducing estimated life expectancies by 5% for men and 7% for women. This method assumes that the underestimation of the real mortality rates in the RLMS is the same for all classes. This is probably not the case as the mortality rates for the manual classes may have been underestimated to a greater extent. Therefore, the estimated gap in the life expectancy between the non-manual and manual classes is conservative. Figure 5.4 presents the corrected class-specific life expectancies at age 15 for men.

The graph shows that for Russian male managers and professionals the life expectancy is about the same as in countries like Hungary, Bulgaria and Slovakia (around 70 years), while for Russian skilled manual workers and supervisors it is close to the average in Ghana, Senegal or Haiti (around 60 years).

For women, the manual/non-manual class gap in life expectancy is smaller. e15 for higher professionals and routine workers is almost the same, although for lower professionals it is about four years higher. e15 for female lower technical workers is about seven years lower than for routine workers. Note that as in the case with mortality rates, the life expectancies for classes with less than ten observed deaths are not reliable.

The inequality pattern for e(20-69) is similar to e15, with the only exception of the relative position of higher and lower professionals.

Table 5.2 also presents e15 and e(20-69) for people who are out of the labour force. Not surprisingly, the life expectancies for this group are considerably lower than for any class. e15 for men in this group is just 33.1 years and for women e15 is 49.9 years.

5.7 Cox proportional hazards models

Cox proportional hazards models let us estimate statistical associations between class and mortality after controlling for a number of variables. As in the previous analyses, the sample is stratified by sex and the models are estimated separately for men and women.

In all previous sections class was coded as a time-constant variable recorded at the time of the first observation. Mortality was estimated for groups of people classified according to their occupation and employment status in the beginning of the market transition in Russia. Class mobility was not taken into account. In this section I introduce this factor, accounting for mobility in two different ways. First, I code class both as a time-varying and time-constant variable and compare the results. Second, I model mobility directly with time-constant class and dummy variables for upward and downward mobility during the follow-up period.

Also I model the association between class and mortality controlling for education and working in the public sector. Finally, I estimate the association between perceived social status and mortality, after controlling for the indicators of social position, such as class, education and household income.

First, I discuss the models for men.

Table 5.3 presents Cox models for the association between class and mortality for time-constant and time-varying class, controlling for the year of death, marital status, ethnicity and the primary sampling unit.

Model 1 presents the associations between time-constant class and mortality. It contains the same information as the standardized mortality ratios that were analyzed above. There are clear differences in mortality between manual and non-manual classes.

Model 2 presents the associations for time-varying rather than time-constant class. Although the coefficients are somewhat different for time-constant and time-varying class, the pattern is the same. The only difference is the relative position of intermediate workers (for men, these are mainly sales representatives and some army officers). With time-varying class, intermediate workers have the lowest mortality hazards. However, there are not many male intermediate workers in the sample, the confidence intervals for the estimates are large, and the difference compared to the reference category (higher professionals) is not statistically significant both for time-constant or time-varying class.

In all subsequent models class is entered as time-constant.

Model 3 adjusts for marital status, ethnicity and the primary sampling unit. The hazard ratios for class remain virtually unchanged compared to model 1. The associations between mortality and marital status and ethnicity are not statistically significant, although it is likely that divorced and widowed men do face greater risks of dying compared to married men (HR=1.15).

Table 5.4 shows some more Cox models for men.

Model 4 estimates class associations with mortality, controlling for education. In other words, the associations between mortality and class are estimated within educational groups and then averaged. The strength of the association between class and mortality reduces after controlling for education, but not considerably. Class remains a statistically significant predictor of mortality, and the pattern remains the same as in models 1 and 3.

Note that our focus in this model is on the hazard ratios for class rather than for education. Education is significantly associated with mortality after controlling for class (with people with higher education having the lowest mortality risks). However, this is the result of estimation of the average effect of education within classes. Clearly, education plays an important role in the selection of people to classes (if education is the "treatment", class is a "post-treatment" variable (Gelman and Hill, 2007)). The hazard ratios for education in model 4 do not take this into account. If estimated without controlling for class, the educational differences in mortality are greater (and perhaps closer to the causal effect of education on the risks of dying).

Model 5 directly estimates the associations between intragenerational class mobility and mortality. In order to do this, I introduce two dummy variables for

Table 5.3: Cox Proportional Hazards Analysis of Class Associations with Risk of Mortality, Russia 1994-2006. Men, 21-70 years old [a]

	Model 1 (Adjusted for age and the year of death, class time-constant		Model 2 (Adjusted for age and the year of death, class time-varying)		Model 3 (Model 1 + adjustment for marital status, ethnicity and region)	
Variable	Hazard Ratio	95% Confidence Interval	Hazard Ratio	95% Confidence Interval	Hazard Ratio	95% Confidence Interval
Occupational Class (ESeC)						
1a/2a.Managers	1.15	0.56-2.36	1.58	0.84-2.97	1.20	0.58-2.47
2a.Higher professionals (ref.)	-	-	-	-	-	-
2b.Lower professionals	1.15	0.66-2.03	1.37	0.77-2.43	1.18	0.67-2.09
3.Intermediate	1.38	0.52-3.64	0.89	0.26-2.98	1.35	0.51-3.58
4/5.Self-employed	1.29	0.67-2.47	1.20	0.57-2.49	1.33	0.69-2.57
6.Lower supervisors	2.35	1.42-3.90	1.91	1.09-3.33	2.34	1.41-3.89
7.Lower sales and service	3.04	1.62-5.71	2.85	1.48-5.48	3.05	1.62-5.75
8.Lower technical	2.18	1.40-3.37	2.32	1.47-3.66	2.16	1.38-3.36
9.Routine	1.92	1.24-2.96	2.19	1.40-3.44	1.86	1.20-2.89
Not in the labour force	7.66	4.89-11.99	3.80	2.37-6.09	7.89	4.99-12.48
Marital status (ref. married)						
Never married					1.06	0.74-1.53
Divorced or widowed					1.15	0.88-1.52
Ethnicity (ref. Russian)						
Non-Russian					0.98	0.76-1.26
No answer					0.97	0.45-2.07
No of Deaths	617		617		617	
No of Persons	6742		6742		6742	
No of Person-years	41951		41951		41951	

[a] Age was set as the analytic time variable. Models 1 and 2 control for the year of death, model 3 controls for marital status, ethnicity, the year of death and primary sampling unit (region); the coefficients for the year of death and the PSUs are not reported.

Table 5.4: Cox Proportional Hazards Analysis of Class Associations with Risk of Mortality, Russia 1994-2006. Men, 21-70 years old [a]

	Model 4		Model 5		Model 6		Model 7	
Variable	Hazard Ratio	95% Confidence Interval	Hazard Ratio	95% Confidence Interval	Hazard Ratio	95% Confidence Interval	Hazard Ratio	95% Confidence Interval
Occupational Class (ESeC)								
1a/2a.Managers	1.16	0.56-2.40	1.19	0.58-2.44	1.25	0.57-2.80	1.20	0.58-2.48
2a.Higher professionals (ref.)	-	-	-	-	-	-	-	-
2b.Lower professionals	1.11	0.62-1.97	1.25	0.71-2.23	1.13	0.59-2.16	1.16	0.65-2.08
3.Intermediate	1.23	0.46-3.28	1.42	0.54-3.77	1.53	0.51-4.56	1.31	0.49-3.48
4/5.Self-employed	1.15	0.59-2.26	1.24	0.64-2.41	-	-	1.12	0.57-2.21
6.Lower supervisors	1.98	1.16-3.39	2.35	1.41-3.93	2.64	1.51-4.59	1.98	1.14-3.42
7.Lower sales and service	2.56	1.32-4.97	3.11	1.64-5.89	3.42	1.68-6.98	2.54	1.29-4.98
8.Lower technical	1.70	1.04-2.79	2.08	1.33-3.25	2.39	1.44-3.95	1.58	0.95-2.61
9.Routine	1.44	0.88-2.36	1.79	1.15-2.79	1.87	1.13-3.09	1.35	0.82-2.24
Not in the labour force	6.24	3.77-10.32	7.50	4.73-11.90	-	-	5.51	3.30-9.20
Education								
Less than secondary	1.40	1.10-1.79					1.36	1.07-1.74
Lower vocational (*PTU*)	1.25	0.99-1.57					1.25	0.99-1.58
Secondary completed (ref.)	-	-					-	-
Specialized secondary	0.92	0.69-1.22					0.96	0.72-1.28
University degree	0.86	0.61-1.21					0.93	0.66-1.31
Mobility (ref. not mobile)								
Upwardly mobile			0.50	0.28-0.89			0.55	0.31-0.99
Downwardly mobile			0.55	0.25-1.22			0.54	0.24-1.20
Public sector (ref. private)					0.99	0.80-1.22		
Logged household income per capita (mean = 0, sd = 1)							0.91	0.83-0.99
Perceived social status								
Perceived wealth (mean = 0, sd = 1)							1.26	1.14-1.40
Perceived power (mean = 0, sd = 1)							0.94	0.84-1.05
Perceived respect (mean = 0, sd = 1)							1.01	0.93-1.09
No of Deaths	617		617		390		617	
No of Persons	6742		6742		5459		6742	
No of Person-years	41951		41951		36032		41951	

[a] Age was set as the analytic time variable. Class is time-constant. All the models control for marital status, ethnicity, the year of death and the PSU; the coefficients are not reported.

Table 5.5: Cox Proportional Hazards Analysis of Class Associations with Risk of Mortality, Russia 1994-2006. Women, 21-70 years old [a]

	Model 1 (Adjusted for age and the year of death, class time-constant		Model 2 (Adjusted for age and the year of death, class time-varying and region)		Model 3 (Model 1 + adjustment for marital status, ethnicity)	
Variable	Hazard Ratio	95% Confidence Interval	Hazard Ratio	95% Confidence Interval	Hazard Ratio	95% Confidence Interval
Occupational Class (ESeC)						
1a/2a.Managers	1.59	0.57-4.45	0.92	0.34-2.48	1.59	0.56-4.50
2a.Higher professionals (ref.)	-	-	-	-	-	-
2b.Lower professionals	0.73	0.35-1.54	0.48	0.24-0.97	0.72	0.34-1.53
3.Intermediate	1.30	0.59-2.85	0.81	0.38-1.72	1.22	0.55-2.68
4/5.Self-employed	1.07	0.30-3.76	0.29	0.04-2.14	1.14	0.32-4.04
6.Lower supervisors	0.72	0.23-2.21	0.35	0.08-1.52	0.68	0.22-2.09
7.Lower sales and service	1.46	0.74-2.89	0.98	0.52-1.85	1.42	0.71-2.82
8.Lower technical	2.66	1.28-5.53	1.70	0.85-3.43	2.67	1.27-5.60
9.Routine	1.59	0.87-2.92	1.20	0.71-2.06	1.60	0.87-2.97
Not in the labour force	5.63	3.07-10.35	2.32	1.34-4.02	6.02	3.24-11.20
Marital status (ref. married)						
Never married					0.72	0.37-1.43
Divorced or widowed					1.16	0.85-1.57
Ethnicity (ref. Russian)						
Non-Russian					0.72	0.44-1.18
No answer					1.81	0.65-5.01
No of Deaths	216		216		216	
No of Persons	7675		7675		7675	
No of Person-years	49420		49420		49420	

[a] Age was set as the analytic time variable. Models 1 and 2 control for the year of death, model 3 controls for marital status, ethnicity, the year of death and primary sampling unit (region); the coefficients for the year of death and the PSUs are not reported.

Table 5.6: Cox Proportional Hazards Analysis of Class Associations with Risk of Mortality, Russia 1994-2006. Women, 21-70 years old [a]

	Model 4		Model 5		Model 6		Model 7	
Variable	Hazard Ratio	95% Confidence Interval	Hazard Ratio	95% Confidence Interval	Hazard Ratio	95% Confidence Interval	Hazard Ratio	95% Confidence Interval
Occupational Class (ESeC)								
1a/2a.Managers	1.29	0.45-3.71	1.70	0.60-4.83	1.23	0.33-4.66	1.41	0.49-4.08
2a.Higher professionals (ref.)	-	-	-	-	-	-	-	-
2b.Lower professionals	0.62	0.29-1.33	0.74	0.35-1.56	0.69	0.28-1.65	0.65	0.30-1.40
3.Intermediate	0.83	0.36-1.91	1.30	0.59-2.88	0.83	0.29-2.37	0.88	0.38-2.06
4/5.Self-employed	0.81	0.22-2.94	1.08	0.30-3.84	-	-	0.77	0.21-2.80
6.Lower supervisors	0.44	0.14-1.40	0.74	0.24-2.28	0.84	0.26-2.76	0.45	0.14-1.46
7.Lower sales and service	0.89	0.42-1.90	1.48	0.74-2.96	1.50	0.66-3.40	0.89	0.41-1.91
8.Lower technical	1.57	0.70-3.54	2.69	1.28-5.65	2.15	0.78-5.92	1.48	0.65-3.37
9.Routine	0.96	0.48-1.93	1.60	0.86-2.97	1.59	0.74-3.39	0.91	0.45-1.84
Not in the labour force	3.93	1.97-7.83	5.88	3.16-10.94	-	-	3.56	1.77-7.15
Education								
Less than secondary	0.73	0.49-1.09					0.71	0.47-1.06
Lower vocational (*PTU*)	0.96	0.62-1.49					0.94	0.61-1.45
Secondary completed (ref.)	-	-					-	-
Specialized secondary	0.53	0.35-0.82					0.54	0.35-0.84
University degree	0.41	0.23-0.73					0.41	0.23-0.75
Mobility (ref. not mobile)								
Upwardly mobile			0.48	0.15-1.56			0.55	0.20-1.53
Downwardly mobile			0.47	0.17-1.31			0.41	0.13-1.35
Public sector (ref. private)					1.13	0.73-1.74		
Logged household income per capita (mean = 0, sd = 1)							0.94	0.80-1.10
Perceived social status								
Perceived wealth (mean = 0, sd = 1)							0.99	0.83-1.18
Perceived power (mean = 0, sd = 1)							1.03	0.86-1.25
Perceived respect (mean = 0, sd = 1)							1.20	1.05-1.38
No of Deaths	216		216		93		216	
No of Persons	7675		7675		5551		7675	
No of Person-years	49420		49420		38456		49420	

[a] Age was set as the analytic time variable. Class is time-constant. All the models control for marital status, ethnicity, the year of death and the PSU; the coefficients are not reported.

upward (from a manual to a non-manual class) and downward (from a non-manual to a manual class) mobility. These measures are rough and imperfect; however, the sample size does not allow us to conduct a more precise estimation.

Interestingly, both men who experienced upward or downward class mobility in the period of market transition have considerably lower mortality risks compared to immobile men (controlling for the class of origin), although, strictly speaking, the effect for downward mobility is not statistically significant at the conventional level. This is consistent with the previous findings by Denisova (2010) who found a negative association between labour market mobility (defined as repeated entry and exit from self-employment) and the risks of dying. In contrast, Billingsley (2009) found a positive association between downward mobility and mortality in Russia. However, Billingsley defined downward mobility as a change on the subjective wealth scale that is quite different from the labour market definition that I used.

Descriptively, the groups of men who changed job during the market transition have lower mortality risks. This is the case for manual workers who moved to non-manual occupations as well as for non-manual workers who took up manual jobs. The result for downwardly mobile men seems counter-intuitive. However, many non-manual occupations in the 1990s were poorly paid and were affected by wage arrears. Moving to a better-paid manual occupation could indeed have a positive effect on health.

Causally, these results can be interpreted in two ways. First, occupational mobility by itself could have a positive effect on health. Second, mobile men could have some unobserved characteristics (for example, they could be more active, stress resilient, etc.) that could explain their better health.

Model 6 estimates the association between working in the public sector of the economy and mortality (controlling for class and other covariates). The previous two chapters showed that the type of employment contracts depends on the sector of the economy as well as on class. However, this is not the case with mortality. There is almost no difference in mortality hazards between men working in the private and public sectors.[1]

Finally, in model 7 I estimate the association between perceived social status and mortality after controlling for a number of objective indicators of social position (class, education, household income per capita). Denisova (2010) estimates the effect of these variables on mortality with the RLMS data with a joint analysis of men and women. Denisova did not control for occupational class. In her analysis, perceived respect was statistically significantly associated with mortality, and perceived wealth was not.

Stratifying the analysis by sex reveals interesting patterns. For men, perceived wealth has a statistically significant association with mortality even after controlling for all other indicators of social position. Men who think that they are wealthier than others live longer compared to men with the same income, class and education, but with a lower subjective assessment of their wealth.

For women, the pattern is different (see Table 5.6). Perceived respect rather than perceived wealth is associated with mortality. In both cases, the effects are not particularly strong, but they indicate differential mechanisms that may affect mortality for men and women.

In model 7 for men, class, education, household income per capita and perceived wealth are all statistically significantly associated with mortality. This shows that for not one of these variables, can the effect be explained entirely by the variation in other observed indicators of social position.

Note that in all models the hazard ratios for class are quite stable (although they do become smaller in the models that control for education).

To compare the strength of the association with mortality for four indicators of social position for men (class, education, household income and perceived wealth),

[1]Note a smaller sample for model 6. The sector of the economy was not always possible to code, especially in the cases where I used retrospective information to code occupation.

I estimate a series of bivariate Cox models. The hazard ratios are shown in Figure 5.5.

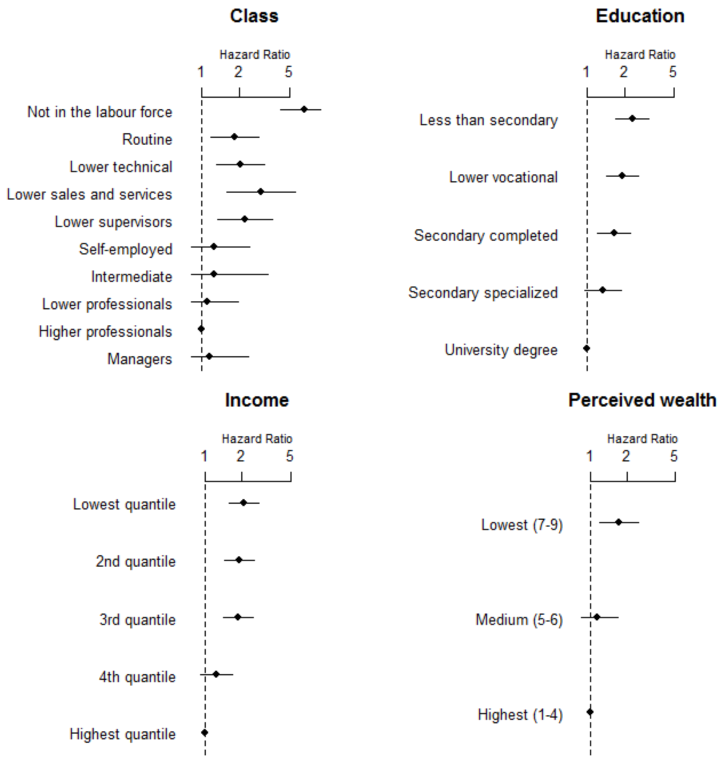


Figure 5.5: Mortality hazard ratios by class, education, household income per capita and perceived wealth. Adjusted for age. Men, 21-70 years old. Estimates plotted with the 95% confidence intervals.

For class, education, and household income the hazard ratios for the least vs. the most privileged groups are about the same and equal about two (apart from the people who are not in the labour force in the case of class). For perceived wealth, the inequality in mortality is somewhat smaller.

Tables 5.5 and 5.6 present the same Cox models for women. As the number of deaths in the female sample is smaller than for men, the estimates are less reliable and there is a higher probability that some differences result purely from chance.

The gap in mortality between manual and non-manual classes is less clear for women than for men. To check if it exists, I grouped all manual and non-manual classes together and compared their mortality risks with a Cox model. The difference between manual and non-manual classes is statistically significant

(HR=1.61, 95% CI: 1.14-2.29), but it is smaller than for men (HR=1.77, 95% CI: 1.39-2.26). The difference between HRs for men and women is not statistically significant, though.

For women, as well as for men, the sector of the economy is not associated with mortality. Both downwardly and upwardly mobile women have lower mortality risks compared to the immobile.

5.8 Class gap in mortality in Russia compared to other European countries

In this section I compare the size of the class gap in mortality in Russia with other European countries.

White et al. (2007) and Langford and Johnson (2009) estimate the class differentials in mortality in England and Wales with the data from the Office for National Statistics Longitudinal Survey for 2001-03 (ONS-LS). The class-specific mortality rates in England and Wales compared to Russia in the same age groups are presented in Table 5.7.

The class-specific mortality rates in England and Wales were calculated with the National Statistics Socio-Economic Classification (NS-SeC) that is very close to the ESeC (in fact, both schemes were created by the same group of researchers)(Rose et al., 2003). The schemes are not identical (for example, the NS-SeC does not have a separate category for lower sales and service workers), but they are close enough to make meaningful comparisons. White et al. (2007) provide separate estimates for managers, higher and lower professionals, while Langford and Johnson (2009) do not separate managers and professionals. This introduces some degree of inconsistency in the comparison of the mortality rates for women in England and Wales and Russia. However, given that the mortality rates for managers and professionals are similar, this is unlikely to seriously bias the results.

Table 5.7: Class mortality rates in Russia compared to England and Wales[a]

ESeC/NS-SeC	England and Wales, 2001-03, standardized rate per 100,000 men, 25-64	England and Wales, 2001-03, standardized rate per 100,000 women, 25-59	Russia, 1994-2006, crude rate per 100,000 men, 25-64	Russia, 1994-2006, crude rate per 100,000 women, 25-59
1a/2a.Managers[b]	219	NA	947	121
1b.Higher professionals[b]	210	116	761	130
2b.Lower professionals[b]	249	142	781	160
3.Intermediate	251	152	768	207
4/5.Self-employed	285	127	542	220
6.Lower supervisors	348	181	1404	199
7.Lower sales and service	NA	NA	1578	277
8.Lower technical/semi-routine	409	183	1441	431
9.Routine	443	220	1319	366
ratio 9/1b (95% CI)[c]	2.1	1.9	2.0 (1.3-3.3)	2.8 (1.1-7.4)
ratio 8/1b (95% CI)[c]	1.9	1.6	2.1 (1.3-3.4)	3.4 (1.2-9.8)
coefficient of variation[d]	0.29	0.23	0.35	0.45
Gini coefficient	0.15	0.12	0.19	0.23

[a] Source: White et al. (2007), Langford and Johnson (2009), based on the ONS Longitudinal Study; author's calculations based on the RLMS.

[b] For women in England and Wales, in Langford and Johnson (2009), managers and professionals were not separated and class was coded as 1.Higher managers and professionals and 2.Lower managers and professionals.

[c] The Russian rate ratios were stratified by age. The 95% confidence intervals for the Russian rate ratios were calculated with the Mantel-Haenszel-type method, as implemented in Stata's command `stmh`.

[d] $CV = \frac{\sigma}{\mu}$, where σ is the standard deviation and μ is the mean.

The English and Welsh mortality rates were age-standardized with the direct method. As the RLMS sample is much smaller than in the ONS-LS, the direct standardization was not possible and I used crude mortality rates for Russia. To achieve comparability, I limited the sample to the age group of 25-64 years for men and 25-59 years for women. As this excludes from the sample the oldest people who have the highest mortality risks, the confidence intervals for the RLMS mortality rates become larger, especially for women. However, this still allows us to estimate the approximate size of the class mortality gap in Russia and compare it to England and Wales.

Several findings follow from the comparison. The male mortality rates in the age group 25-64 years are more than three times larger in Russia than in England and Wales. In other words, male life expectancy is much lower in Russia. The differences in female mortality rates in the age group 25-59 are smaller. In non-manual classes, women in Russia have only 10% to 30% higher mortality rates than in England and Wales. For manual classes, the gap is larger. For female routine workers the mortality rate in Russia is almost two times higher than in England and Wales. These contrasts underestimate the true difference between Russia and England and Wales, as the mortality rates in the RLMS are 17% lower than the official mortality rates for men and 39% lower for women.

I also compare the lower technical and routine vs. higher professionals mortality rate ratios in the two countries. The Russian rate ratios were adjusted for the age differences between classes.

In England and Wales, male routine and lower technical (semi-routine in the NS-SeC) workers have about two times higher mortality rates than higher professionals. In Russia these ratios are similar. For women in England and Wales, the lower technical and routine to higher professionals ratios are somewhat lower than for men. In Russia the female ratios are larger than the male and about two times higher than the female ratios in England and Wales. However, as the estimates for

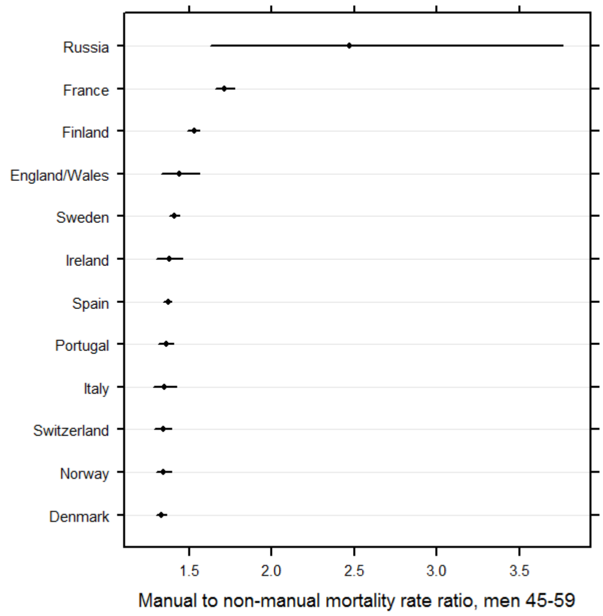


Figure 5.6: Manual to non-manual mortality rate ratios (with 95% CIs) in several European countries and Russia. Men aged 45-59. The rate ratios adjusted for the exclusion of people for whom class was not coded, as proposed by Kunst et al. (1998). The data for Russia are for 1994-2006; for European countries for different periods in the 1980s. Sources: Kunst et al. (1998), author's calculations based on the RLMS.

Russian women aged 25-59 are based on very small numbers, especially for some classes, this result should be taken with caution.

The lower technical and routine to higher professionals ratios describe the size of inequality between the extremes of the class structure. To assess the inequality across the whole distribution, I use two standard measures of inequality, the coefficient of variation (CV) and the Gini coefficient. Both the CV and Gini coefficients in Russia are larger than in England and Wales, suggesting a somewhat larger class gap in mortality in Russia. Note also that the absolute rather than relative class gap in mortality (given by the differences between class mortality rates rather than the ratios) is much larger in Russia than in England and Wales.

Another way to compare the size of the class gap in mortality is to combine classes into manual and non-manual groups and calculate the rate ratio. Kunst

Table 5.8: Manual to non-manual mortality rate ratio in several European countries and Russia, men[a]

Country	manual to non-manual rate ratio and 95% CI, with (*without*) adjustment 30-44	45-59	60-64	30-64
Finland	1.76 (1.70-1.83)	1.53 (1.49-1.56)	1.32 (1.27-1.37)	
	1.60 (1.54-1.67)	*1.36 (1.32-1.39)*	*1.13 (1.08-1.18)*	
Sweden	1.66 (1.59-1.75)	1.41 (1.38-1.44)	NA	
	1.48 (1.40-1.56)	*1.26 (1.23-1.29)*	*NA*	
Norway	1.65 (1.57-1.74)	1.34 (1.30-1.39)	1.28 (1.24-1.33)	
	1.49 (1.41-1.58)	*1.22 (1.18-1.27)*	*1.15 (1.11-1.20)*	
Denmark	1.53 (1.47-1.59)	1.33 (1.30-1.36)	1.21 (1.18-1.24)	
	1.43 (1.37-1.49)	*1.24 (1.21-1.27)*	*1.12 (1.09-1.15)*	
England/Wales	1.46 (1.24-1.74)	1.44 (1.33-1.56)	1.33 (1.22-1.45)	
	1.38 (1.16-1.66)	*1.40 (1.29-1.52)*	*1.29 (1.18-1.40)*	
France	NA	1.71 (1.66-1.77)	1.50 (1.44-1.56)	
	NA	*1.65 (1.60-1.71)*	*1.44 (1.38-1.50)*	
Ireland	1.43 (1.28-1.59)	1.38 (1.30-1.46)	NA	
	1.31 (1.16-1.47)	*1.32 (1.24-1.40)*	*NA*	
Switzerland	1.45 (1.36-1.55)	1.34 (1.29-1.39)	NA	
	1.43 (1.34-1.53)	*1.32 (1.27-1.37)*	*NA*	
Italy	1.35 (1.25-1.46)	1.35 (1.28-1.42)	NA	
	1.18 (1.08-1.29)	*1.10 (1.03-1.17)*	*NA*	
Spain	NA	1.37 (1.34-1.39)	NA	
	NA	*1.18 (1.15-1.20)*	*NA*	
Portugal	1.50 (1.42-1.59)	1.36 (1.31-1.40)	NA	
	1.38 (1.30-1.47)	*1.25 (1.20-1.29)*	*NA*	
Russia	**2.13 (1.29-3.53)**	**2.47 (1.63-3.76)**	**1.31 (0.73-2.38)**	**2.05 (1.57-2.69)**
	1.97 (1.19-3.27)	***2.29 (1.51-3.48)***	***1.22 (0.68-2.20)***	***1.90 (1.45-2.49)***

[a] Estimates were adjusted for the exclusion of people for whom class was not coded with the method proposed by Kunst et al. (1998). Unadjusted estimates are given in italics. The data for Russia are for 1994-2006; for European countries for different periods in the 1980s. The 95% confidence intervals for the Russian rate ratios were calculated with the Mantel-Haenszel-type method, as implemented in Stata's command `stmh`. Sources: Kunst et al. (1998), author's calculations based on the RLMS.

et al. (1998) provide the estimates for manual to non-manual mortality gaps in eleven European countries based on census and survey data collected in the 1980s. The estimates were provided only for men in three age groups (aged 30 to 44, 45 to 59 and 60 to 64). The rate ratios were adjusted for the exclusion of economically inactive people as described in section 5.4.

I use the same method to estimate the manual to non-manual mortality rate ratio in Russia. However, contrary to Kunst et al. (1998), who separated non-manual, manual and agricultural workers, I included agricultural workers in the manual group (except for a few self-employed farmers who together with the other self-employed were coded as non-manual workers). The ESeC version that I use does not have a separate class for agricultural workers and they cannot be separated from other manual occupations without applying a more detailed occupational classification.

The SMRs for farmers and agricultural workers in the study by Kunst et al. were found to be lower than average and closer to the non-manual rather than manual occupations. Therefore, including them in the manual group could widen the manual/non-manual mortality gap. This potential bias is not likely to be large in Russia. First, the proportion of agricultural workers in Russia is low. Second, most agricultural workers are not independent farmers, but unskilled employees in large agricultural firms and their mortality rates are likely to be close to those of manual workers.

The manual to non-manual mortality rate ratios for men in several European countries compared to Russia are presented in Table 5.8. In age groups 30 to 44 and 45 to 59 the Russian rate ratios are noticeably larger than the European ratios. In the age group 60 to 64 there is no large difference, but the estimates for this group for Russia are based on small numbers and are less reliable.

The data sets used in the study by Kunst et al. have much larger samples than the RLMS, and therefore, the rate ratios have narrower confidence intervals. The confidence intervals for the Russian rate ratios are much wider. Unfortunately, Kunst et al. only provide the estimates for three age groups separately and not for all men aged 30 to 64 (in the latter case, a more precise comparison would have been possible).

For some European countries the estimates in age groups 30 to 44 and 60 to 64 are missing. In age group 45 to 59 the rate ratios for all countries are available. The rate ratios, adjusted for the exclusion of economically inactive people, are plotted in Figure 5.6 along with the 95% confidence intervals. Despite the wide confidence interval, the rate ratio for Russia is statistically significantly larger than for most European countries. While in the majority of the European countries the manual to non-manual mortality rate ratio for men aged 45-59 is under 1.5, in Russia it is likely to be somewhere between two and three.

5.9 Discussion

In this chapter I investigated class-based differentials in mortality in Russia. Several conclusions follow.

The mortality rates in Russia are different across occupational classes, with non-manual classes facing lower mortality risks than manual classes. This finding is not particularly surprising as class differentials in mortality were previously found in many other countries (Elo, 2009; Kunst et al., 1998). However, in Russia class inequality in mortality appears to have some specific characteristics.

First, the mortality risks of higher and lower professionals in Russia are similar. Female lower professionals even have somewhat lower mortality rates and higher life expectancy at age 15 than female higher professionals. In England and Wales, higher professionals have lower mortality rates than lower professionals.

Perhaps the similarity of the mortality risks of higher and lower professionals in Russia can be explained by the disadvantaged position of traditional intelligentsia professions (engineers, medical doctors, university lecturers) during the market transition. The earnings of higher professionals were relatively low, especially compared to Western professionals. Gerber and Hout (1998) mention low returns to education as a specific feature of both the Soviet and post-Soviet stratification orders. In the 1990s, the situation for higher professionals deteriorated compared to Soviet times. Most doctors, scientists and university lecturers were employed in the public sector and this was underfunded. The Russian engineering industry could not sustain open competition with Western technologies without state support. There is anecdotal evidence of widespread downward social mobility among Russian higher professionals in the 1990s and the downgrading of their social status. Low earnings in combination with psychological stress could increase the mortality risks of Russian higher professionals.

Note that if we look at the working age population only, the crude mortality rates for lower professionals are higher than for higher professionals (Table 5.7) and life expectancy between ages 20 and 69 is lower (Table 5.2). This may reflect the differential impact of the market reforms on the mortality of higher and lower professionals in different birth cohorts, with older higher professionals experiencing larger risks than younger.

Another unusual feature of class inequality in mortality in Russia is the lower mortality rates of routine workers compared to the lower technical (skilled) manual workers. In England and Wales, skilled manual workers live longer than unskilled; in Russia this seems to be the other way around. Most lower technical workers in Russia are employed in industry and this experienced a deep economic crisis during the market transition. In the USSR industrial workers were well paid and enjoyed economic and social privileges. This changed dramatically in post-Soviet Russia and may have caused the deterioration of the health of skilled industrial workers.

The relatively high mortality rates of higher professionals and skilled industrial workers (compared to England and Wales) may be explained by the differential impact of the market reforms on different sectors of the Russian economy. It would be hard to notice these effects if the educational rather than class inequalities in mortality were analyzed. However, the sample size in the RLMS is relatively small for the studies of mortality and the statistical power of the analysis is low. The findings need to be checked with larger samples.

Previous studies conducted in other countries found mixed evidence on the relative size of the class gap in mortality for men and women depending on the measures of social position, health, and the national context (Elo, 2009). If inequality is measured in absolute rather than relative terms, it is greater for men than for women. If relative measures are applied, the inequality is often found to be similar for both genders.

This study provides mixed results for the comparison of the size of the mortality gap for men and women, too. As in other countries, the absolute differences in mortality rates are larger for Russian men. This is a consequence of the male mortality rates in Russia being much higher than the female. As for the relative measures, the manual/non-manual gap in mortality is greater for men than for women, as shown by Kaplan-Meier survival curves in Figure 5.3. Compared to male inequality in mortality, female inequality is to a lesser degree structured along the manual/non-manual lines (Figure 5.3). On the other hand, if the inequality in mortality is measured in the working age population only and as the rate ratio of routine or lower technical workers to higher professionals, it seems to be larger for women than for men (Table 5.7). A larger sample size is required to reach more definite conclusions.

Compared to Western European countries, the manual to non-manual gap in male mortality is significantly larger in Russia, even taking into account the uncertainty in the estimates (Table 5.8 and Figure 5.6). This is consistent with Mackenbach et al. (2008) who previously found a larger educational gap in mortality in Eastern European countries compared to Western Europe.

Mackenbach et al. (2008) provide several explanations for the cross-national differences in the inequality in mortality. These are the large social inequalities in smoking and hazardous drinking in some countries and the differential access to health care.

More than 60% of Russian men smoke (McKee et al., 1998; Bobak et al., 2006). As in other countries, there are social differences in the prevalence of smoking. In 2004, 40% of men with a university degree smoked, compared to 63% of men with secondary education and 73% of men with primary education (Bobak et al., 2006). This inequality seems to be larger than in Western Europe (Giskes et al., 2005). Note, however, than in 1996 social inequality in male smoking in Russia was much smaller (the difference between men with university degree and primary education was 14% rather than 33% (Bobak et al., 2006)). This suggests that educational inequality in smoking in Russia may be strongly affected by the heterogeneity of educational distributions across birth cohorts and the analysis of trends in educational inequality should take into account the size of educational groups. Overall, it is unlikely that smoking alone can account for the difference in the size of the class gap in mortality between Russia and Western Europe.

Hazardous drinking is a more plausible explanation. Some estimates attribute from 30% to 40% of deaths among working age Russian men to the direct or indirect effects of alcohol consumption (Leon et al., 2009). Hazardous drinking is known to be strongly associated with education (Leon et al., 2007; Tomkins et al., 2007; Leon et al., 2009). Further research is necessary to analyze the association of class with alcohol consumption and the contribution of alcohol to class inequality in mortality, but available evidence suggests that they are likely to be large.

The unequal access to health care for different classes can also contribute to the mortality gap, although a separate analysis is required to test this hypothesis.

The main limitation of this study is a limited sample size. As a result, the estimates have a high degree of uncertainty. It is also not possible to compare the size of the class inequality in mortality in different periods of the market transition and analyze the dynamics of inequality.

Finally, it is worth noting that the main goal of this chapter was to estimate class differentials in mortality in Russia rather than analyze causal mechanisms that relate to class and the risks of dying. The identification of the causal effect of class on mortality would be an interesting problem that, however, requires different data and statistical techniques.

Chapter 6

An Occupational Status Scale for Russia

It is not necessary to be a social scientist to know that the social status of occupations varies. Some occupations are more respected in society than others, and people who belong to high- and low-status occupations differ with respect to their lifestyles and the cultural norms that they share. Since Weber and Veblen, the social scientists who have been interested in status inequalities have produced a variety of scales that aim to account for the differences in occupational status.

Note the difference between the class and the occupational scales approaches to measuring social inequality. According to the class approach, all people can be divided into several classes based on their occupation, employment and supervisory status. Then the class variable is usually applied in some form of regression analysis where class is entered as a categorical variable. The previous three chapters of this thesis used this research strategy for the study of occupation-based inequality in Russia.

Instead, the proponents of the second approach construct occupational scales with various kinds of statistical techniques that I describe later in this chapter. These scales can then be entered into the substantive statistical analysis as continuous variables. Until recently, the two approaches were hardly compatible.[1]

Most of the research on occupational scales has been focused on the USA and Western European societies as data for those societies are usually both of a better quality and more easily accessible. Occupational status in other parts of the world has been studied only to a limited degree. The aim of this chapter is to construct and validate an occupational scale for Russia.

Russia is a country with a long tradition of status inequalities. The differences in the social status of aristocracy, merchants, intelligentsia and peasants were an important part of everyday life in imperial Russia. One of the aims of the Russian revolution of 1917 was to eradicate status inequalities. In one of their first decrees the Bolsheviks abolished estates and all related privileges and limitations. In the 1920s and 1930s the Communist government, in what amounted to an affirmative action policy, promoted people with working-class and peasant backgrounds, while opportunities for the educated classes were systematically restricted (Fitzpatrick, 1979).

Social equality was one of the key elements of the official Soviet ideology that claimed that class inequalities were absent in the USSR. At the level of the official rhetoric, manual workers had high prestige and social standing. But in reality the status hierarchy existed and did not necessarily favour manual workers.

In 1950-51, in the course of the Harvard project on the Soviet social system, about 2,100 Soviet refugees who lived in Munich and in the USA were asked to rate thirteen occupations according to their desirability. This was the first study of occupational prestige in the USSR. The occupations were ranked in the following order (from the most to the least desirable): doctor, scientific worker, engineer, factory manager, foreman, accountant, armed forces officer, teacher, rank-and-file worker, brigade leader (farm), party secretary, collective farm chairman, collective farmer (Inkeles and Bauer, 1959, p.77). As is evident from this list, non-manual

[1] In their recent papers Chan and Goldthorpe (2004, 2007a) combined the two approaches. I discuss their work in section 6.1.

occupations (intelligentsia) were ranked higher than manual.

In the 1960s Soviet sociologists conducted several studies of occupational prestige. In 1963 Shubkin and his colleagues from Novosibirsk surveyed 3,000 secondary school pupils who were asked to rate 74 occupations on the 10-point scale. In the resulting scale scientific and engineering occupations were ranked at the very top, while manual jobs in industry, construction and transportation occupied intermediate positions, and occupations in agriculture and sales and services were assigned the lowest social standing (Yanowitch and Dodge, 1969, p.623). Some white-collar occupations (such as sales personnel, clerks, accountants and bookkeepers) were ranked remarkably low.

Another survey of secondary school students was administered by Vodzinskaya in Leningrad in 1964. This is the survey that Treiman (1977) used in his cross-national study of occupational prestige. At the top of Vodzinskayas prestige scale were scientists, doctors and other professionals. Skilled manual and agricultural labourers were ranked significantly lower. Remarkably, non-manual service, sales and clerical occupations were ranked even lower than agricultural occupations.

Treiman compared Soviet and Eastern European prestige scales with the international scale and concluded that in socialist countries manual occupations were ranked somewhat higher and clerical occupations were, on the contrary, downgraded (Treiman, 1977, p.146).

I am not aware of any studies of occupational status conducted in the USSR or Russia since the 1960s.[2] Did the socialist experience have any long-term effect on the status hierarchy in Russia? Given the continued inertia from the socialist past, we could expect skilled manual occupations to be ranked higher and clerical occupations to be ranked lower in Russia compared to other countries. However, as shown in this chapter, the occupational status order in contemporary Russia is very similar to that of Western industrial countries, with only minor differences

[2] An exception is the CAMSIS scale described below.

found.

6.1 Approaches to the study of the occupational hierarchy

The major goal of this study is to construct an occupational scale for Russia. There are three major approaches to constructing occupational scales: prestige scales, socio-economic indices and relational scales.

The literature on occupational scales may be divided into several groups depending on the theoretical and methodological preferences of the authors. There is a large number of studies of occupational prestige based on surveys, in which respondents were asked to rate or rank different occupations according to their prestige or desirability. Another research tradition constructs socio-economic occupational scales on the basis of the joint effect of occupational education and income. A number of studies derived an occupational scale from the analysis of the marriage and friendship structure across occupational groups. Here I review each of these approaches in more detail. The review includes only some of the most important works; for a more detailed discussion and classification of approaches see Grusky and van Rompaey (1992) and, for prestige and socio-economic scales, Hauser and Warren (1997).

The fact that occupations are associated with different degrees of social prestige has long been noticed by researchers. Early empirical studies of occupational prestige appeared before WWII, and they were followed by more systematic research in the 1950s and 1960s. In 1947 a prestige survey was conducted in the USA by the National Opinion Research Centre (NORC) (although the results were published only in 1961). The NORC survey was replicated in 1963 (Hodge et al., 1964) and served as the basis for a detailed occupational scale constructed by Siegel (1971). In 1989 the NORC General Social Survey again included a module on occupational prestige, and the scale was upgraded (Nakao and Treas, 1994).

In Britain a detailed occupational scale was constructed by Goldthorpe and Hope (1974). Early cross-national comparative studies of occupational prestige were conducted in the 1950s (Inkeles and Rossi, 1956). In 1977 Treiman (1977) published his seminal study, in which occupational prestige scales for 60 societies were compared.

Theoretically, many of the studies of occupational prestige were based on the analysis of the consequences of the division of labour in the society. Due to the division of labour, which is necessary in a developed economy, different occupations exist. They require different skills and lead to the varying levels of control over scarce resources that results in occupational differences in power and privilege. Power and privilege are the source of the prestige associated with occupations (Treiman, 1977, p.5). This argument states that occupational prestige is based on material and symbolic job rewards.

In terms of the methods applied, the studies of occupational prestige are similar. A group of respondents was usually asked to rank or rate a number of occupations in respect of their prestige, social standing or general desirability. The samples used in these studies vary from nationally representative to local samples of university students or high school graduates. After surveys were conducted, mean values for the occupations were calculated and ranked to form a scale. In case of cross-national studies, the scales for different countries were then correlated.

These studies demonstrated that the degree to which the ranking of occupations depends on the social position of respondents was very limited. Men and women, members of different ethnic, age and occupational groups tend to agree on the position of different occupations in the social hierarchy. This justifies the use of non-representative (especially student) samples in research on occupational prestige.

Occupational prestige scales also appeared to be remarkably stable over time. Correlation between the Nakao-Treas scale (based on the 1989 survey) and the Siegel scale (based on the data from 1963-64) was 0.97 (Nakao and Treas, 1994). For the 1963 replication of the NORC study and the original 1947 version correlation between the scales was even higher, 0.99 (Hodge et al., 1964).

The cross-national studies of occupational prestige showed that the resulting scales were similar across the world. Treiman (1977) demonstrated that the average correlation between the prestige scales for two random countries was about 0.8. Inkeles and Rossi (1956) reported similar results for six countries that they studied. Treiman argued that these findings supported the structural model of prestige determination, since the consequences of the division of labour and the unequal distribution of power and privilege were similar in different countries. The cultural hypothesis, which claimed that the prestige hierarchy was culturally specific, was rejected. On the basis of the cross-national comparison, Treiman constructed an international scale of occupational prestige (Treiman (1977); the scale was updated in Ganzeboom and Treiman (1996)) and can be used in comparative research.

Several criticisms were raised against the studies of occupational prestige. Perhaps the most important critical comment questioned the validity of the methodology applied. It was argued that direct survey questions about the prestige of occupations did not in fact measure prestige, but rather some kind of "general desirability" of jobs. When asked to rate occupations according to their prestige, respondents performed the task with a "rather unspecific 'better-worse' dimension" in mind (Goldthorpe and Hope, 1974, p.11). It is indeed rather difficult to check what respondents actually mean when they assess the "prestige" or "social standing" of occupations in a survey.

Another problem with occupational prestige surveys is more practical. Since a large number of occupations must be rated, these surveys are expensive and can hardly be conducted on a regular basis. While reliable prestige scales exist for the United States and a few more countries, in other countries the scales include only a limited number of occupations. Even if the average correlation between occupational prestige hierarchies for two random countries is high, some countries may show considerable variation, especially for particular occupations. Besides, many occupational prestige surveys were conducted in the 1950s and 1960s. The prestige scales are stable over time, but they do change (Nakao and Treas, 1994), and for most of the countries the data would not allow us to study the dynamics of occupational prestige.

Another type of occupational scale, widely used in social stratification research, is based on the measurement of the joint effects of occupational education and income. Perhaps the most famous of these scales is the Duncan Socio-Economic Index (SEI) (Duncan, 1961). Duncan's original task was to estimate the prestige scores for the occupational titles not available in the 1947 NORC study. In order to do this, he assumed that educational level and income were two main determinants of occupational prestige. Then he regressed NORC prestige scores[3] on income and education, and using the regression formula, estimated the scores for the occupations that were missing in the NORC study.[4] The Duncan SEI was widely used in status attainment research as the indicator of the social standing of occupations (for the most well-known example see Blau and Duncan (1967)).

The Duncan SEI was updated several times for different occupational classifications and prestige scales (Hauser and Warren, 1997, pp.191-193). Technical procedures required to calculate the index became more sophisticated, but the essence remained the same, namely, regression of prestige scores on occupational education and income. Ganzeboom et al. (1992) proposed an alternative method

[3]More precisely, the percentage of "excellent" and "good" ratings for each occupation.

[4]The Duncan's formula was SEI= $0.59 * income + 0.55 * education - 6$, where income was defined as a percentage of those reporting an income of \$3500 or more in 1949, and education as a proportion of high school graduates. Both income and occupation were adjusted by the occupational age composition.

for calculating SEI that did not use prestige scores to estimate the weights for occupational education and income. The idea was to look at occupation as an intervening mechanism between education and income. People go to the school to get better jobs, and better jobs are paid better. The model for SEI was specified to maximize the indirect effect of education on income (through occupation) and at the same time minimize the direct effect. Technically, this was done through a series of regressions. The relationship between education, income and occupation was adjusted by age, as the same jobs can be paid differently depending on the age of their holders and the average educational level and occupational structure varied across age groups. Women were excluded from the analysis, because they were not represented in some of the datasets the authors used. As the data came from the International Stratification and Mobility File, which at that moment included 31 datasets from 16 nations for the period from 1968 to 1982, the resulting index was international and it may be used in comparative research.

Although the method for constructing the International SEI differs from the more traditionally calculated SEIs, its interpretation is the same. Its authors claim that "the advantages of our procedure over the older one are simply that (a) the logical relationship with prestige is completely eliminated and (b) it gives a clearer interpretation to SEI" (Ganzeboom et al., 1992, p.12). Even when prestige scores are used to estimate SEI, substantively SEI is a weighted combination of occupational income and education, where education has somewhat greater effect than income. At least one practical advantage of the new methodology is clear. We can construct SEI for the nations where a detailed prestige scale is missing.

Comparing prestige and socio-economic scales, Featherman and Hauser (1976) reported that in the status attainment models SEI provided a better model fit than prestige scales. This finding was interpreted as evidence of the occupational stratification being socio-economic in its nature. It was argued that prestige scales were only an "error-prone" estimate of the socio-economic attributes of occupations (Featherman and Hauser, 1976, p.405).

SEI may have a good explanatory power in status attainment models, but it was criticized on theoretical grounds. Education and income are quite different indicators of the social position of individuals, and they are not necessarily well correlated. While both occupational income and education are powerful predictors in many stratification models, it is not obvious that a weighted combination of them will do an equally good job in predicting various social outcomes. Hauser and Warren conclude their article, in which they analyzed the properties of the socio-economic scales, with a cautionary comment: "If there is any general conclusion to be drawn from the present analysis, it is that we ought to move toward a more specific and disaggregated appraisal of the effects of occupational characteristics on social, psychological, economic, political and health outcomes. While composite measures of occupational status may have heuristic uses, the global concept of occupational status is scientifically obsolete" (Hauser and Warren, 1997, p.251).

The third approach to the construction of occupational scales (the one that I apply in this chapter) is based on the analysis of marriage or friendship structure. These scales are usually called relational or network scales.

The assumption of relational occupational scales is that people tend to form intimate associations (friendship and marriage) with those who are equal in terms of social standing. Thus, using data on frequencies of intimate associations between occupations one can derive a scale that shows relative occupational distances. Contrary to SEI or prestige scales, relational scales do not depend on occupational income, education or subjective rankings of prestige, but only on the structure of "real-life" associations.

Since the 1960s, there has been a large number of studies that used the relational approach to construct occupational scales (Laumann, 1966, 1973; Oldman and Illsley, 1966; Stewart et al., 1973; Feldman and El Houri, 1975). Those studies employed different types of data (on marriage, friendship or social mobility) as well as various statistical techniques, usually either multidimensional scaling, correspondence analysis or Goodman's RCII modelling. However, despite all technical differences, the approach has remained essentially the same.

In recent years, two teams of researchers have produced relational scales for a number of countries. First, following initial research by Stewart et al. (1973, 1980) the Cambridge (or CAMSIS) scale has been upgraded for the UK and constructed for some other countries (Prandy and Lambert, 2003; Prandy and Jones, 2001). Second, as part of their project on cultural consumption in the UK Chan and Goldthorpe (2004) constructed a status scale that later was replicated at the international level (Chan, 2010). While statistical procedures used in both projects were similar, the interpretation of resulting scales differed substantially.

The authors of the CAMSIS scale treat the resulting scale as a measure of unidimensional generalized social advantage, both economic and cultural (Bottero and Prandy, 2003). They argue in favour of using the scale instead of the traditional class approach. On the contrary, Chan and Goldthorpe follow the Weberian distinction between class and status and interpret their scale as a measure of social status in contrast to social class. According to them, social class is relevant for the economic life-chances of individuals, while status matters for life-styles and cultural consumption (Chan and Goldthorpe, 2004, 2005, 2007c,d,b,a; Chan, 2010).

Another difference between the scales is that CAMSIS scales have two separate sets of scores for men and women. In contrast, in Chan and Goldthorpe's status scale scores are common for both sexes. While CAMSIS scales take several hundred occupations as units of analysis, status scales in most cases deal with more aggregated occupational groups.

A CAMSIS scale exists for Russia (Prandy, 2003). It was constructed with data from two waves of the RLMS. In an attempt to increase the sample size Prandy and his colleagues analyzed not only married couples, but all cross-gender couples found in the same household. However, the analytical sample still included only 4,800 pairs, which is a relatively small sample for this type of analysis, especially if undertaken at the level of detailed occupational groups. Given these limitations, the CAMSIS scale for Russia is probably less reliable than for other countries.

In this chapter I do not intend to resolve the difference between the interpretations given to the social status and CAMSIS scales. It is not possible on the basis of the analysis that I undertake. The aim is to construct a relational scale and compare it with other possible scales. I leave aside the question of whether this scale can indeed be used along with social class in social stratification research or whether it represents the same dimension of social inequality as social class.

6.2 Data and methods

There are several requirements for the data that can be applied to construct relational scales. First, the data must have detailed information on the occupations of respondents and their alters (either partners or friends). Second, the sample size must be large enough to allow for a meaningful statistical analysis of the contingency table of the occupations of respondents and friends or partners. While technically the analysis is possible even with small samples, uncertainty around the estimates will be large in this case, in particular if the occupational classification is based on a large number of groups.

The RLMS that has been used for constructing the CAMSIS scale for Russia satisfies the first condition, but does not satisfy the second. As the RLMS is a panel study, pooling samples across the waves would not considerably increase the sample size.

As an alternative to the RLMS in this study I use the Russian part of the International Social Survey Programme (ISSP)[5]. Details about the ISSP can be found in chapter 1.

[5]The RLMS is used for validation purposes in section 6.8.

Occupation in the ISSP is coded according to the four-digit level of ISCO88, an international occupational classification developed by the ILO. Data on occupation are available for respondents and their spouses. To increase the sample size I pool the data for 15 years, from 1992 to 2006, and the final analytic sample size is 8016 couples.

To construct a scale from the data on occupations of spouses I use the statistical technique known as Goodman's RC type II model (Goodman, 1979; Powers and Xie, 2000). This is a log-multiplicative model that assumes that categories in both rows and columns are ordered, but their exact ordering is unknown to the analyst. The model assigns scores to rows and columns that describe the association between them in the best possible way. Alternatively, the model can be described as Poisson regression with the multiplicative row-column interaction term. In its most general form the model can be formally expressed as

$$\log F_{ij} = \mu + \mu_i^R + \mu_j^C + \beta\phi_i\varphi_j \tag{6.1}$$

where F_{ij} is a frequency in the ij-cell of a contingency table, μ is a grand mean effect, μ_i^R and μ_j^C are marginal effects of rows and columns respectively, β is an association parameter and ϕ_i and φ_j are row and column scores (that we are mainly interested in).

To estimate model 6.1 we have to set normalization constraints. All RCII models in this chapter were first estimated in ℓEM (Vermunt, 1997) and the following constraints were applied: $\Sigma\phi_i = 0, \Sigma\varphi_j = 0, \sigma_\phi = 1, \sigma_\varphi = 1$. However, ℓEM cannot estimate standard errors for the parameters in the multiplicative interaction term. This can be done in the *gnm* package in R (Turner and Firth, 2007). *gnm* uses other conventions to overcome the identification problem. In the final model that was estimated in R, I identified the coefficients and standard errors, setting the coefficient for the reference group (army offcers) to zero.

The input for an RCII model in our case is a contingency table where occupations of men are row categories and occupations of women are column categories. In all subsequent analysis, the categories for occupations of men and women are the same and input tables are square. The frequency in the ij-cell (F_{ij}) represents the number of married couples, where a husband is in the occupational group i and a wife is in the occupational group j.

6.3 Selection of the model

Model 6.1 can be modified in several ways. First, people in the same occupational group may have a higher probability of marrying within the group than predicted by model 6.1. In social mobility research, the main diagonal of mobility tables usually requires special treatment. In our case we can model this effect as well:

$$\log F_{ij} = \mu + \mu_i^R + \mu_j^C + \alpha_{ij}\delta_{ij} + \beta\phi_i\varphi_j \tag{6.2}$$

where $\delta_{ij} = 1$ if $i = j$ and δ_{ij}=0 if $i \neq j$ and α_{ij} is a parameter for the effect of the main diagonal.

Models 6.1 and 6.2 assume two separate sets of scores for rows and columns, in other words, different status scores for men and women in the same occupation. As we have a square table with the same occupational units in rows and columns, we can constrain scores for men and women to be equal. That would yield model 6.3 (without the term for the diagonal effect) and model 6.4 (with the term for the diagonal effect).

$$\log F_{ij} = \mu + \mu_i^R + \mu_j^C + \beta\phi_i\phi_j \tag{6.3}$$

$$\log F_{ij} = \mu + \mu_i^R + \mu_j^C + \alpha_{ij}\delta_{ij} + \beta\phi_i\phi_j \tag{6.4}$$

In all these models we assume that the solution is unidimensional. However,

Table 6.1: Model fit for models 1-5

No	dim[a]	diag[b]	equal[c]	*df*	L^2	*BIC*	Δ^d
1	1	No	No	1024	1811	-7394	0.14
2	1	Yes	No	990	1181	-7719	0.11
3	1	No	Yes	1056	1839	-7654	0.15
4	1	Yes	Yes	1022	1220	-7967	0.11
5	2	Yes	Yes	990	1137	-7762	0.10

[a] Number of dimensions.
[b] Effect of the main diagonal.
[c] Row and column scores equal.
[d] Dissimilarity index (proportion of incorrectly classified cases).

Model 6.4 can be extended to the RC(M) model that does not make this assumption.

$$\log F_{ij} = \mu + \mu_i^R + \mu_j^C + \alpha_{ij}\delta_{ij} + \sum_m \beta_m \phi_{im}\phi_{jm} \tag{6.5}$$

Substantively model 6.5 implies that the association between the occupations of husbands and wives can be explained by several uncorrelated factors (dimensions).

Which model should we choose? I have fitted all the models for a 34x34 contingency table of occupations of husbands and wives. (See section 6.4 for a discussion of occupational classifications). The results are presented in Table 6.1.

To choose the best model I use the Bayesian Information Criterion (BIC) (Raftery, 1995). BIC is based on the maximized value of the likelihood function for the estimated model, but it penalizes for the number of degrees of freedom that were used. The models with a smaller BIC should be preferred. Table 6.1 shows that the models with the diagonal effect (6.2 and 6.4) fit the data better than the models without it (6.1 and 6.3) and the models with equal scores for men and women (6.3 and 6.4) should be preferred to the models with different scores (6.1 and 6.2). The one-dimensional solution (6.4) is statistically better than the two-dimensional (6.5). Therefore, model 6.4 should be preferred to the others.

6.4 Construction of occupational groups

An important issue for occupational scales is the level of precision in the construction of occupational groups. A limited sample size in most cases does not allow us to produce precise status scores for all possible occupations. First, some occupations are rare and may not be well represented in the sample. We simply do not have enough cases to estimate meaningful status scores for them. Second, including too many occupations would lead to a very sparse contingency table. For instance, if we estimate the model for 500 occupations the contingency table would have 25,000 cells. Given the sample of 8,016 couples the average number of cases per cell would be less than one.

Therefore, some aggregation of occupations is inevitable. The degree of aggregation and the number of occupational categories used in the analysis may vary.

In this chapter, I follow an empirical approach to selecting the degree of the precision of the occupational classification. In the original ISSP data set, occupations are coded at the four-digit ISCO88 level (approx. 390 unit groups). I aggregated the four-digit unit groups in three different ways: (a) into 133 groups (four-digit level, some units merged within the same three-digit group), (b) into 86 groups (three-digit level, some units merged within the same two-digit group, some bigger units split at the four-digit level), (c) into 34 groups (two-digit level, some units split at the three-digit level[6]).

Separate status scales were estimated for each occupational classification. To choose the classification that fits the data better I apply the following validation procedure.

First, we would expect occupational status to be well correlated with education. Chan (2010) showed that correlation between status scales and education is strong

[6]In two cases I split the groups at the four-digit level, separating medical doctors from other health and life science professionals and economists from other social scientists. The "economist" in Russia is an occupational label usually used for middle-level business professionals.

Table 6.2: Pearson's correlations between the scales with 34, 86 and 133 occupational units[a]

	34 units	86 units	133 units
34 units	1		
86 units	0.94	1	
133 units	0.86	0.91	1

[a] At the four-digit ISCO88 level.

in the countries that he and his colleagues studied.

Second, the ISSP contains two questions on subjective assessment of a position in the social hierarchy that are related to the concept of social status. People were asked to attribute themselves to one of the following social classes or strata[7]: 1. Lower, 2. Working, 3. Lower middle, 4. Middle, 5. Upper middle, 6. Upper. This question is available in the Russian questionnaire in 1992-2001. In 2003, 2005 and 2006 another question was asked: "In our society there are people who occupy high social position, and there are people who occupy low social position. According to your opinion, which place do you occupy on this scale at the moment?", with possible answers ranging from 1 ("Highest") to 10 ("Lowest").[8]

As all three occupational scales measured with a different degree of precision are measurements of the same concept, we expect that the "best" scale would show higher correlations with education, subjective social class and self-placement on the social hierarchy scale. Lower correlations would indicate more measurement error.

Table 6.2 shows correlations between the scales based on three various occupational classifications. Table 6.3 shows correlations between the scales and validation variables.

The scale based on 34 occupational unit groups is better correlated with education and subjective social class than the other two scales (both at the individual

[7]The exact wording of the question varied for different years.
[8]For the convenience of the analysis the scale has been reversed.

Table 6.3: Pearson's correlations between occupational scales and validation variables

	individual level			group level[a]		
	educ.[b]	subj. class[c]	self-plac.[d]	educ.[e]	subj. class[f]	self-plac.[g]
34 units	0.56	0.45	0.19	0.91	0.93	0.61
86 units	0.55	0.44	0.19	0.87	0.89	0.65
133 units	0.54	0.42	0.18	0.83	0.83	0.64

[a] Mean status at 86 unit level.
[b] Number of years spent in educational institutions.
[c] 6-point scale, from "Lower" to "Higher", treated as continuous.
[d] Self-placement on the 10-point scale of perceived social position, from "Lowest" to "Highest".
[e] Proportion with higher education.
[f] Proportion of middle class and higher.
[g] Proportion with self-placement > 4.

and group levels), although the difference in correlation coefficients between the scales is not very large. The self-placement in the social hierarchy is the only variable, with which the scale based on 86 groups is better correlated. However, correlation between status and self-placement variables is much lower than between status, education and subjective social class for all three versions of the status scale. In fact, as shown in section 6.6, the self-placement variable is affected by occupational earnings. If we compare occupational status scales with education and subjective class, the two variables that are most closely connected with status, the scale based on 34 occupational groups should be preferred.

6.5 Status scales for men and women

In section 6.3 I showed that the model with separate sets of status scores for men and women provides a worse fit to the data than the model with equal scores, at least at the 33-group level of disaggregation. The substantive analysis confirms this result. Although the difference in correlations with the validation variables between models with equal and different scores is very small, in all cases correlations are higher for the model with equal scores (see Table 6.4).

Table 6.4: Status scales with equal and different scores for men and women correlated with the validation variables[a]

	individual level			group level		
	educ.	subj. class	self-plac.	educ.	subj. class	self-plac.
equal scores	0.56	0.45	0.19	0.91	0.93	0.61
different scores	0.55	0.44	0.18	0.90	0.93	0.60

[a] Model with 34 occupational groups. All variables measured as in Table 6.3.

6.6 Properties of the occupational status scale

The final version of the scale for Russia is presented in Figure 6.1 and Table 6.5.[9]

In their study of the status order in the UK Chan and Goldthorpe (2004) showed two characteristics of the status scale. First, non-manual occupations rank higher than manual, while occupations of mixed non-manual/manual character are in the middle of the status hierarchy. Second, within the non-manual part of the status scale professionals rank higher than managers.

An examination of the Russian scale confirms both results. There is a clear tendency for non-manual occupations to rank higher than manual.[10] Professionals are ranked higher than general and corporate managers.

In previous research on relational occupational scales, occupational scores were produced without confidence intervals. The recently written *gnm* package for R allows to estimate uncertainty around the status scores. Figure 6.1 shows the estimates with 95% confidence intervals. To overcome the problem of the reference category in the presentation of the results, I use quasi standard errors, as suggested by Firth (2003).

The first four positions on the scale are occupied by professionals: university lecturers, scientists, lawyers and medical doctors. These are traditional intelli-

[9] A routine for coding occupational status from ISCO88 for Stata is available on my personal website (`http://sites.google.com/site/bessudnov`).

[10] Obviously, the statistical technique that I use does not indicate which end of the scale is "higher" or "lower". However, it is reasonable to assume that university professors have higher occupational status than agricultural labourers.

Table 6.5: Occupational status scale for Russia

	Occupational group	Abbr.	Typical occupations	ISCO88	n men	n women	% of women	Status score
1	Higher education teaching professionals	HET	University lecturers	231	51	63	55	0.84
2	Science and IT professionals	SIT	Computer programmers, physicists, chemists	211, 212, 213	54	67	55	0.64
3	Legal professionals	LEG	Lawyers	242	35	43	55	0.54
4	Medical doctors	DOC	Medical doctors	2221, 2222	80	132	62	0.52
5	Professionals in information services and arts	INF	Librarians, archivists, journalists	243, 244, 245, 246 (exc.2441)	61	172	74	0.13
6	Managers of small enterprises	MSE	General managers	13	211	104	33	0.12
7	Corporate managers	CMN	Directors, department managers	12	283	146	34	0.11
8	Engineers and architects	ENG	Engineers, architects	214	542	368	40	0.11
9	Senior officials	OFF	Senior officials	11	33	20	38	0.11
10	Business professionals	BPR	Accountants, economists	241, 2441	94	550	85	0.00
11	Military	ARM	Armed forces	01	101	20	17	0.00
12	Teaching professionals (primary and secondary)	TEA	School teachers	23 (exc.231)	175	769	81	0.00
13	Other associate professionals	OAP	Bookkeepers, admin. secretaries, buyers, etc.	34	350	436	55	-0.16
14	Engineering associate professionals	EAP	Quality inspectors, technicians, etc.	31	215	282	57	-0.42
15	Other life science and health professionals	LSP	Agronomists, pharmacists, veterinarians	22 (exc. 2221 and 2222)	53	129	71	-0.44
16	Office clerks	CLR	Secretaries, library clerks, typists	41 (exc.413)	55	333	86	-0.48
17	Life science and health associate professionals	LAP	Medical assistants	32	19	435	96	-0.50

Table 6.5: Occupational status scale for Russia (continued)

	Occupational group	Abbr.	Typical occupations	ISCO88	n men	n women	% of women	Status score
18	Customer services clerks	CSC	Cashiers, counter clerks, receptionists	42	16	161	91	-0.53
19	Teaching associate professionals	TAP	Pre-primary teachers	33	21	180	90	-0.66
20	Precision and handicraft workers	PHW	Instrument and glass makers, engravers	73	41	35	46	-0.75
21	Salespersons	SAL	Shop salespersons	52	99	635	87	-0.78
22	Personal and protective services workers	PSW	Cooks, child-care workers, police officers	51	377	506	57	-0.84
23	Stationary plant operators	SPO	Weaving-machine operators, petroleum-plant operators	81	151	114	43	-0.95
24	Semi-skilled workers nec.	SSW	Semi-skilled workers not elsewhere classified	84	43	34	44	-0.96
25	Craft and related trades workers	CWO	Wood treaters, weavers, sewers	70, 74	103	309	75	-1.02
26	Metal and machinery workers	MMW	Flamecutters, tool-makers, motor-vehicle mechanics	72, 75	1524	302	17	-1.03
27	Material-recording and transport clerks	MTC	Stock, production and transport clerks	413	47	192	80	-1.05
28	Drivers and mobile plant operators	DRV	Car, bus and lorry drivers, motorised farm operators	83	1562	130	8	-1.12
29	Skilled agriculural workers	SAW	Dairy and poultry producers, forestry workers	61	160	261	62	-1.17
30	Machine operators and assemblers	MOA	Mechanical assemblers, sewing-machine operators	82	123	149	55	-1.19
31	Extraction and building trades workers	EBW	Carpenters, plumbers, building electricians	71	808	162	17	-1.22
32	Sales and services elementary occupations	SEO	Cleaners, doorkeepers, building caretakers	91	236	551	70	-1.30
33	Labourers in construction, transport and manufacturing	LCM	Freight-handlers, hand packers	93	226	164	42	-1.40
34	Agricultural labourers	ALB	Farm-hands and labourers	92	67	62	48	-1.56

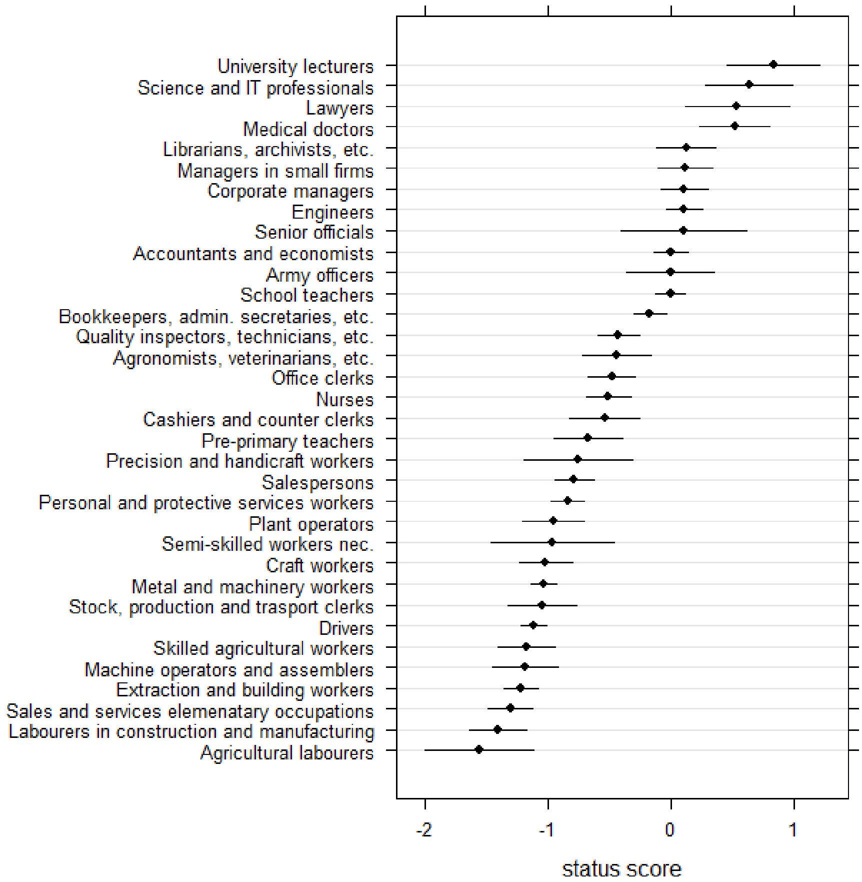


Figure 6.1: The occupational status scale for Russia. The estimates with 95% confidence intervals.

gentsia professions, also ranked at the top of the social hierarchy in the prestige scales of the 1960s. These are followed by a group of occupations whose scores on the scale are very close: a heterogeneous group of professionals in information services (such as librarians, archivists, journalists, artists), general and corporate managers, engineers, senior officials (note large confidence intervals). The next group consists of accountants and economists (as mentioned before, the latter are mid-level business professionals in Russia), armed forces officers and school teachers, followed by bookkeepers, administrative secretaries and other associate professionals. All occupations in the top half of the scale are non-manual, with a clear division between professionals and managers.

The middle part of the scale (from quality inspectors and technicians to personal and protective services workers) consists of occupational groups that have a mixed, both non-manual and manual character. The only exceptions are health and life science professionals who mainly live in the countryside (agronomists and veterinarians). Skilled and non-skilled manual workers are in the bottom part of the scale.

Confidence intervals allow us to visually examine the uncertainty in the differences between groups. While the exact order of the groups should be taken with caution, in general the scale is reliable. However, the confidence intervals around smaller groups are quite high. This is an argument against using a more detailed occupational classification, at least with the present sample size.

Let us explore the association between occupational status and class. Figure 6.2 shows the distribution of occupational status scores across ESeC classes. There is a clear pattern of association between class and status. Managers and higher professionals have the highest median status, followed by lower professionals and intermediate workers, the self-employed and lower sales and service workers, lower supervisors and technicians and lower technical workers. Routine workers have the lowest median status score. It is also clear from figure 6.2 that some classes (managers, lower sales and service, routine) are homogeneous in terms of occupational status, while other classes (higher and lower professionals and in particular the self-employed) are more heterogeneous.

In section 6.4 I have shown that occupational status is well correlated with education, subjective social class and self-placement on the ten-point scale of social hierarchy. Now I explore these relationships in detail.

Figure 6.3 shows a scatter plot of occupational status vs. occupational education. As can be seen from the graph, the association between status and education is very strong (r=0.94).[11]

[11] In other countries studied in Chan (2010) correlations between occupational status and education at the group level are also very high, ranging from 0.78 (the UK) to 0.96 (the US).

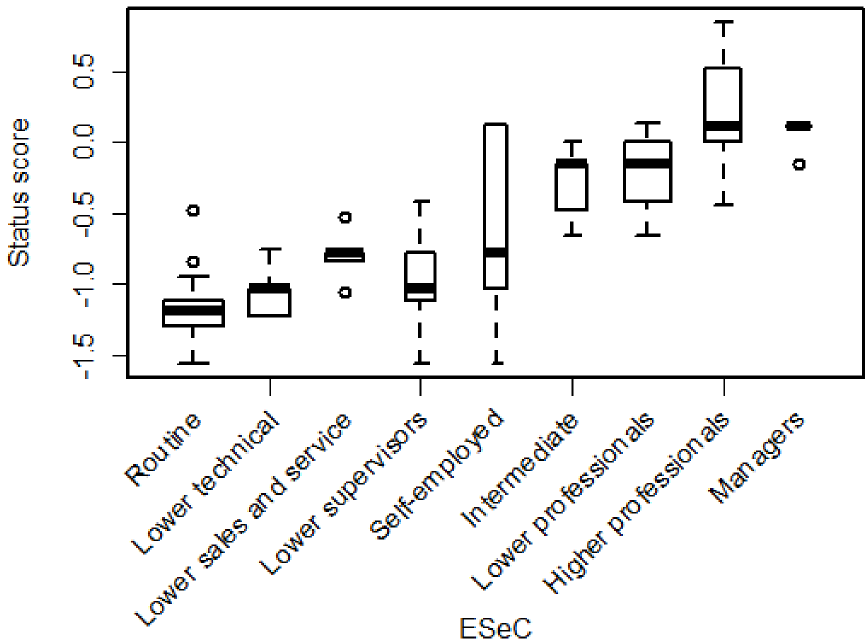


Figure 6.2: The distribution of occupational status scores across occupational classes. RLMS 2006

To explore the relationship between occupational status and occupational earnings I produce two separate graphs for men and women to account for the effects of occupational segregation and gender gap in earnings (Figures 6.4 and 6.5). In both cases the association between occupational status and earnings is weaker compared to status and education, though for women the association between status and earnings is noticeably stronger than for men. Some occupational groups with a higher proportion of well-educated people (university lecturers, doctors) have high status scores despite relatively low occupational earnings.[12] On the other hand, some relatively well-paid manual occupations (for example, male craft workers or female construction workers) are low on the status scale.

[12]Relatively low earnings of medical doctors and university lecturers are specific for Russia, at least compared with the US and Western Europe. The graphs suggest interesting gender differences in occupational earnings. The pay of male doctors is much lower than that of male legal and business professionals, while for women the earnings of all those groups are closer to each other. Perhaps this difference can be explained by the fact that most doctors work in the public sector where employers have much less discretion in setting individual contracts.

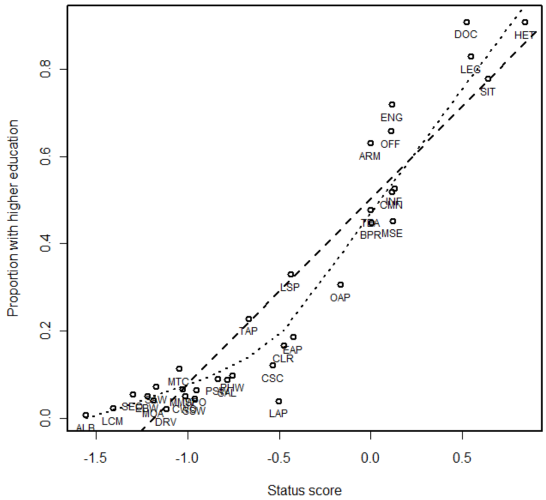


Figure 6.3: Occupational status vs. proportion with higher education (r=0.94). The dotted line is a lowess curve.

In this chapter I do not aim to explore in detail the relationship between occupational status and earnings beyond a simple bivariate analysis. Occupational earnings inequality in Russia is a complex phenomenon that is driven not only by gender occupational segregation, but to a large extent by unequal distribution of occupations across the private and state sectors of the economy as well as regional inequalities. However, even a simple bivariate analysis suggests that assortative mating in Russia is primarily driven by educational and cultural rather than material resources (cf. Kalmijn, 1994). In fact, correlation between occupational status and the proportion of people with higher education in Russia (as well as in other countries) is so high that it would be reasonable to suggest that educational differences are the main driving force for occupational assortative mating.

A question arises as to why the relational status scale cannot be replaced with a much simpler scale constructed on the basis of occupational education (for instance, the proportion of people with a college degree). Indeed, such a scale would be a useful proxy for occupational status. However, for several reasons, it would not be a perfect approximation. First, there are occupational groups that are quite different in terms of education (as defined by the proportion of people

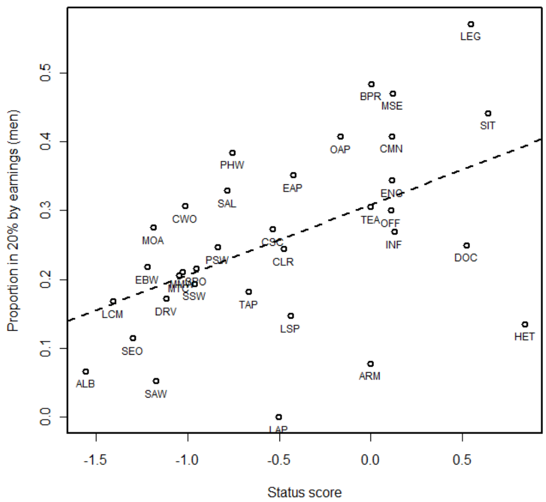


Figure 6.4: Occupational status vs. occupational earnings (men, r=0.50)

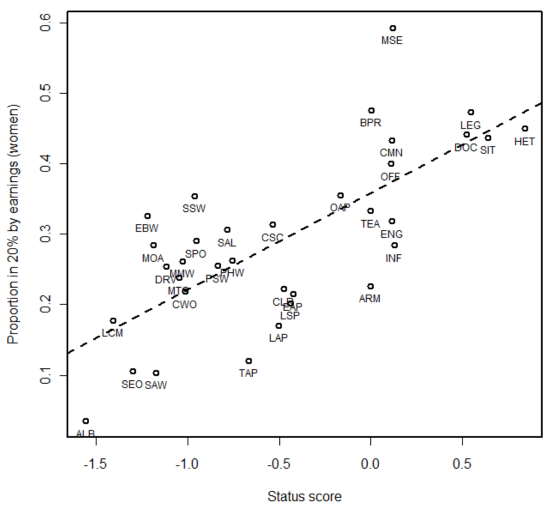


Figure 6.5: Occupational status vs. occupational earnings (women, r=0.72)

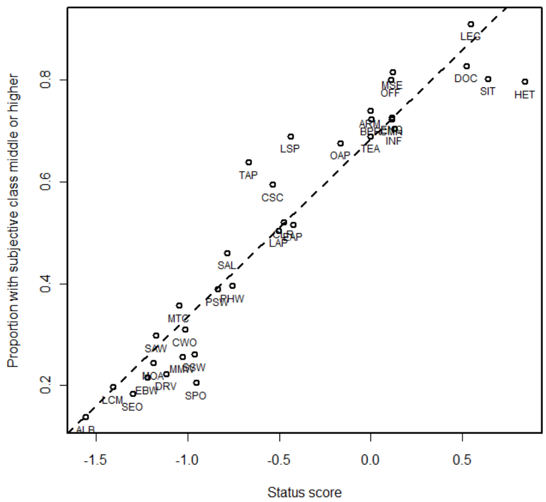


Figure 6.6: Occupational status vs. subjective social class (r=0.95)

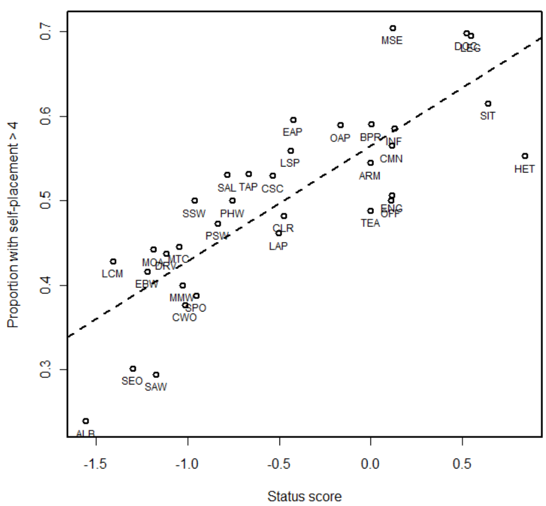


Figure 6.7: Occupational status vs. self-placement on the 10-point scale (r=0.81)

with a university degree), but close on the status scale (for example, engineers and general managers). Second, it is hard to find a variable that summarizes occupational education well. While occupational groups at the top half of the status scale are clearly different with regard to the proportion of people with a university degree, low status occupational groups do not substantially differ on this variable, probably because vocational education is more relevant for them than higher education. Using the mean number of years spent in education does not solve the problem as it is less reliable and fails to distinguish between different educational tracks. Third, because of educational expansion in the 20th century, there are more people with a university degree in recent cohorts. This can bias a scale that is based solely on educational achievements.

Let us now compare occupational status with two other validation variables, subjective social class and self-placement on the 10-point scale of perceived social hierarchy (Figures 6.6 and 6.7). As can be seen from Figure 6.6, status and subjective social class are very well correlated (r=0.95). High correlations of occupational status, education and subjective class confirm the validity of the occupational status scale.

On the other hand, correlation between occupational status and the self-placement variable is lower (r=0.81). If we regress both subjective class and self-placement variables on status and occupational earnings, earnings will only be a statistically significant predictor for self-placement. This suggests that earnings mainly affect how individuals place themselves on the numerical social hierarchy scale, but are less important for their subjective social class.

6.7 Status scales in Russia and the United States

A prima facie comparison of the Russian scale and status scales previously produced for other countries does not give any evidence of major differences between Russia and Western countries. A more formal comparison is impossible, as the occupational classifications used for the construction of national scales are different.

To overcome this problem I construct a scale for the USA using exactly the same analytic procedures as for the Russian scale. The data come from the pooled General Social Survey data set for 1988-2008. The GSS is a member of the ISSP project, and data collections procedures and sample sizes are similar in the GSS and in the Russian part of the ISSP.[13] After pooling the data for 1988-2008 the analytic sample consists of 14,037 couples. Occupational groups have been constructed in the same way as in the Russian case. The only difference is that group SSW ("semi-skilled workers not elesewhere classified") is not present in the USA sample, as the ISCO88 code for it (84) is not part of standard ISCO88 and was used only in the Russian part of the ISSP. Therefore, the scale for the USA includes 33 occupational groups.[14]

The resulting scale for the USA is very similar to the Russian scale ($r = 0.91$).[15] Figure 6.8 shows the scatter plot of the USA vs. Russian status scores.[16]

The differences between the scales for two countries are minor. Medical doctors, life science professionals, teaching associate professionals and salespersons rank higher in the USA than in Russia. Science and IT professionals, managers of small enterprises, officers in the armed forces and stationary plant operators rank higher in Russia. Although the differences in the scores of individual occupational groups are to be interpreted with caution, it is still possible to speculate on the reasons behind some of them. For instance, the higher rank of science and IT professionals in Russia is in line with research on occupational prestige in

[13] Unfortunately, it is not possible to construct a scale using the British analogue of the GSS, the British Social Attitudes Survey, as there are too many missing values for occupations of partners in the BSA.

[14] Occupation is coded in the GSS according to the US SOC80. It was converted to ISCO88 using the tool by Ganzeboom and Treiman (2005).

[15] The scale for the USA is not reported in this chapter, but is available on my personal website (`http://sites.google.com/site/bessudnov`).

[16] To produce this plot, I reparametrized the status scale with the identification constraints that are default in ℓEM (see section 6.2). Otherwise we would have to assume that the status scores for the reference category (army officers) are the same in Russia and the USA.

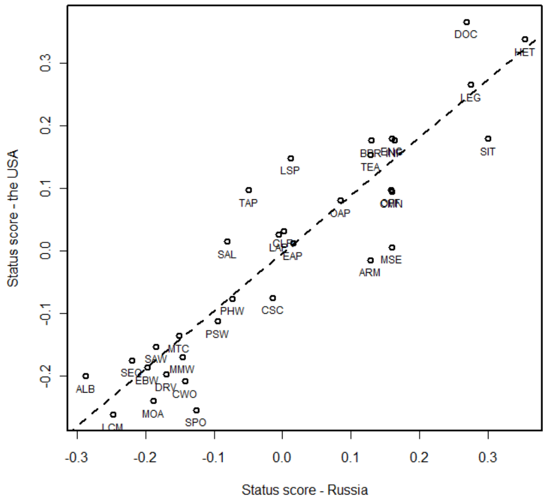


Figure 6.8: Occupational status scores in Russia and the USA (r=0.91)

the USSR in the 1960s (Yanowitch and Dodge, 1969), when scientists were at the top of the occupational prestige hierarchy. Many managers of small enterprises in Russia are self-employed entrepreneurs, an economically privileged social group in post-Soviet Russia (Gerber, 2001a). However, with the present data any definite conclusions about the differences in the positions of occupational groups in the USA and Russia would be hazardous.

6.8 The social status scale and other occupational scales

In this section I compare the occupational status scale with three other scales well-known in stratification research and described in section 6.1. SIOPS is an international scale of occupational prestige, ISEI is an international socio-economic scale and CAMSIS-Russia is a relational scale constructed with the data from the RLMS.

Table 6.6 shows correlations between four scales at the four-digit ISCO88 level. Table 6.7 demonstrates how the scales are related to our validation variables for

Table 6.6: Pearson's correlation for the status scale, ISEI, SIOPS and CAMSIS-Russia[a]

	status	ISEI	SIOPS	CAMSIS (male)	CAMSIS (female)
status	1				
ISEI	0.90	1			
SIOPS	0.83	0.88	1		
CAMSIS (male)	0.82	0.79	0.74	1	
CAMSIS (female)	0.77	0.73	0.65	0.70	1

[a] At the four-digit ISCO88 level.

Table 6.7: Occupational scales correlated with validation variables (ISSP data)[a]

	individual level			group level[b]		
	educ.	subj. class	self-plac.	educ.	subj. class	self-plac.
status	0.57	0.45	0.19	0.91	0.94	0.61
ISEI	0.56	0.43	0.18	0.92	0.90	0.62
SIOPS	0.54	0.40	0.17	0.86	0.84	0.53
CAMSIS	0.51	0.40	0.16	0.87	0.84	0.55

[a] All variables measured as in Table 6.3.
[b] At the 86 group level.

ISSP data. As the status scale was constructed with the ISSP data, it is cross-checked against the data from Round 15 of the RLMS (2006) (Table 6.8).

For the ISSP data the status scale and ISEI outperform SIOPS and CAMSIS. The differences between the status scale and ISEI are very small, although the status scale is better correlated with subjective social class. However, for the RLMS data both SIOPS and ISEI show higher correlations with validation variables than the status scale, although the difference is again quite small.

Figure 6.9 examines substantive differences between the status scale and ISEI, at the level of 34 occupational status groups. Correlation between the scales is very high (r=0.9). There are only minor discrepancies. University lecturers (HET) and science and IT professionals (SIT) rank higher on the status scale than on ISEI. The same is the case for general managers of small enterprises (MSE), a group that in post-Soviet Russia probably includes many self-employed entrepreneurs

Table 6.8: Occupational scales correlated with validation variables (RLMS Round 15)

	individual level		group level[a]		
	rights[b]	respect[c]	educ.[d]	rights[e]	respect[e]
status	0.18	0.13	0.84	0.58	0.52
ISEI	0.19	0.12	0.88	0.65	0.52
SIOPS	0.18	0.13	0.84	0.63	0.56
CAMSIS	0.17	0.10	0.83	0.55	0.32

[a] At the 86 group level.
[b] "Please imagine a nine-step ladder where on the bottom, a first step, stand people who are completely without rights, and on the highest step, the ninth, stand those who have a lot of power. On which of the nine steps are you personally standing today?"
[c] "And now another nine-step ladder where on the lowest step stand people who are absolutely not respected, and on the highest step stand those who are very respected. On which of the nine steps are you personally standing today?"
[d] Proportion with higher education.
[e] Mean values in occupational groups.

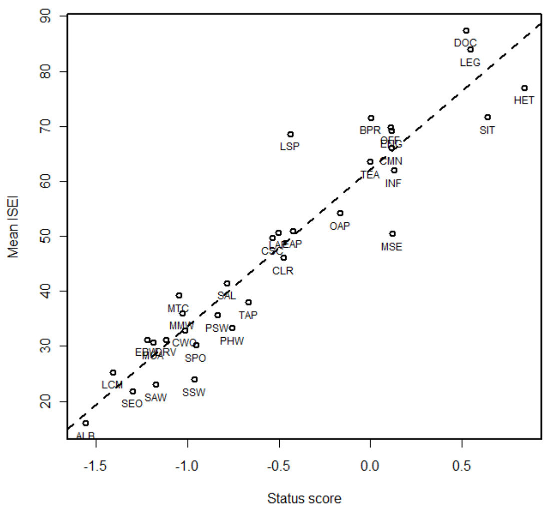


Figure 6.9: The status scale vs. ISEI (34 groups, r=0.9)

who started new businesses after the collapse of the state socialist system. In contrast, life science and health professionals (LSP, a group consisting mainly of veterinarians and pharmacists) are lower on the status scale than expected from their ISEI. This can probably be explained by the fact that many people in this group live in the countryside.

Overall, despite very different approaches and data sets used to construct both scales, the status scale for Russia and ISEI are surprisingly close to each other. This suggests that ISEI may serve as a proxy for status scale in Russia. It is unlikely that the actual differences between these two scales will lead to different conclusions if the scales are used as measures of the occupational status in substantive research.

6.9 Discussion

The analysis shows that the occupational status scale for Russia is similar to the scales previously constructed for Western industrial countries. If we compare the Russian scale with the scale for the USA, only idiosyncratic differences can be found. This finding is trivial and surprising at the same time. After Treiman's (1977) influential book that showed similarity of occupational prestige in different parts of the world, it is hard to expect striking differences in occupational status between Russia and Western countries. However, Treiman did point out some differences in occupational prestige in capitalist and socialist countries, including the USSR. In the latter manual occupations ranked higher. Both in the USSR and post-Soviet Russia the economic position of some occupational groups (for instance, professionals) relative to other groups has been very different from Western countries. Russian professionals, especially employed in the public sector, rarely enjoy the level of earnings and economic stability of their Western colleagues. Besides, there is a perceived common feeling both in Western countries and Russia that Russia is a very specific society with a social structure different from Western countries.

This chapter shows that this is not the case, at least when it comes to occupational status. Perhaps this can be explained by the fact that occupational status is very likely to be driven by occupational education rather than income. Educational requirements for different occupations are similar in different countries, hence the similarity in occupational status orders.

There are several limitations to the findings presented in this chapter. Due to a relatively small sample size, I was forced to aggregate occupations into larger occupational groups. Therefore, the status scale can barely say anything about the social status of several occupations that are not well represented in the sample (e.g. senior officials[17], financial and management consultants, managers of large international firms).

As mentioned earlier, to increase the sample size I pooled the ISSP data sets for 15 years. Due to the nature of existing data this strategy has certain limitations. The status order in Russia may have changed in the last 15 years, years marked by rapid economic and political developments. A comparison of occupational status orders in the late USSR and post-Soviet Russia would be of clear sociological interest; however, we lack data to conduct such a test. I conducted a reliability test and compared status scores for two halves of the sample, 1992-99 and 2000-06. Two scales correlate with $r = 0.91$; no substantially interpretable differences were found. However, given the limited sample size and large uncertainty in estimates, it is hard to come to any definite conclusion with the present data. The labour force survey conducted by the Russian Statistical Office has a sample size that is large enough to estimate occupational status without aggregating occupations into larger groups and would allow us to compare status scales for different years. Unfortunately, at the moment neither these data nor micro-data from the Russian

[17] "Senior officials" occupy the modest ninth position on the scale; however, they are more likely to be middle-level government officers, mainly in Russian regions, rather than top-level federal officials.

census are available for public use.

In studies of this kind it is hard to separate the effect of marital choice based on educational and status homophily, and the effect of structural constraints of the choice. Some occupational groups are spatially segregated and have relatively low chances for social interaction with each other. For example, this is the case with urban and agricultural occupations. I tried to control for structural constraints adding to the model separate terms for the cells on the main diagonal (i.e. cases where a husband and a wife came from the same occupational group and, therefore, had higher probabilities of getting married). However, admittedly this is not a completely satisfactory solution to this problem.

It should also be noted that the studies of occupational status look at the group rather than individual characteristics. In fact, occupation may be only one of the factors that affect a person's status, other factors being race and ethnicity, family background and personal characteristics (also see Gould (2002) for a formal model of individual status).

Despite all these limitations, the occupational status scale that has been constructed for Russia displays good validity and reliability and can be used in further empirical research.

Chapter 7

Conclusion

The goal of this thesis was to explore different aspects of occupation-based inequality in post-Soviet Russia, with a focus on occupational social class. I have addressed the following central questions. Can the occupation-based measures that are frequently used in social stratification research in Western countries (such as occupational class and status) be applied in a meaningful way to the Russian case? What does their application contribute to the study of social inequality in Russia? In this conclusion, I briefly summarize the results of the empirical analysis and discuss their implications for class analysis and social stratification theory in general.

In the literature on the theory of social stratification, the most popular definition of social class to date is in terms of employment relations (Goldthorpe, 2000, 2007a). The theory states that employers offer various types of employment contracts to different groups of employees, depending on the nature of their jobs. In doing so, employers design the most efficient contracts to increase the productivity of employees in various occupations. The differences in employment contracts produce variation in economic stability, security and prospects. Service classes (managers and professionals) have better labour market outcomes than manual classes. The unemployment rates of managers and professionals are lower, their chances for promotion are higher and their salaries increase as they progress in their careers, in contrast to members of the manual classes. A number of empirical studies conducted mainly in Britain have demonstrated these effects.

There is nothing in this theory that makes it nationally specific and confined only to Western European countries and the USA. The nature of work in the same occupations shows little cross-national variation, and rational employers have incentives to design the most efficient employment contracts everywhere in the world. In this respect, Russia should not be very different from the UK.

To study class in Russia, I applied the European Socio-Economic Classification (ESeC), a class schema that was recently designed by a group of researchers on the basis of Goldthorpe's class theory for the use in cross-national studies in Europe (Rose and Harrison, 2010). The schema was successfully validated in European, mainly Western European, countries. Russia is an industrial country with 75% urban population and an occupational structure that is similar, although not identical, to Western European countries. There are no particular theoretical reasons to believe that the ESeC would work in Russia in a radically different way than in Europe.

In chapter 3 I checked this claim empirically. I looked at the class differences in three labour market outcomes: the probability of having an informal employment contract, the index of fringe benefits and the unemployment risks. As all three variables describe the class-relevant aspects of employment contracts, they should be well correlated with occupational class. We would expect that the members of service classes are less often on informal employment contracts than the members of manual classes, as employers are more interested in long-term employment relations with the former than the latter. For the same reason, we expect the service classes to have on average more fringe benefits and lower unemployment risks. The differences in the probability of unemployment were previously used to validate the NS-SeC class schema in Britain (Goldthorpe and McKnight, 2006).

The results showed that the ESeC in Russia is indeed correlated with the three labour market outcomes, in the same way as in Britain. Russian managers and professionals have lower risks of informal employment than manual classes. The classes for which the theory predicts a mixed type of employment contract (intermediate workers and lower supervisors) have medium risks of informal employment (higher than managers and professionals, but lower than manual workers). A similar pattern is observed for fringe benefits and unemployment risks, although in the case of fringe benefits class differences are small. These findings confirm that the ESeC is a valid tool for studying occupation-based inequalities in Russia and works there in the same way as in Western Europe.

Another finding of chapter 3 was that the sector of the economy where workers are employed is associated with the type of employment contract, as measured by three outcome variables. Jobs in the state sector are better protected, especially in large enterprises. In small firms in the private sector employment contracts are the most precarious. For instance, informal employment contracts are virtually non-existent outside small private firms. Moreover, class and the sector of the economy interact, especially for lower sales and service workers, so that the size of the class differences in the outcome variables depends on the sector of the economy.

In chapter 4 I explored two related problems. First, I document the unusual shape, for Western Europe and the USA, of cross-sectional age-earnings profiles in Russia. In Russia, there is little variation in earnings across age groups and, at least for men, workers in their thirties have higher average earnings than older workers. The analysis shows that the theories of the association between age and earnings that are traditional in the economics literature cannot explain the deviation of the Russian profiles from their usual shape. The shape of the profiles in Russia is affected by specific characteristics of the labour market, such as low returns to firm-specific work experience and age segregation. I have provided some evidence to show how age segregation in the labour market that resulted from rapid structural changes in the Russian economy affected the shape of age-earnings profiles.

Second, chapter 4 looked at the shape of class-specific age-earnings profiles. Goldthorpe and McKnight (2006) showed that for the salariat (managers and professionals) in Britain, average earnings of older employees are substantially higher than average earnings of younger employees. On the other hand, for manual classes the age-earnings profiles are almost flat. This demonstrates underlying differences in the type of employment contracts across the classes. Productivity pay and low career prospects in manual classes do not imply the growth of wages over the life cycle. In non-manual classes, employees have higher chances of promotion, and their earnings substantially rise with the experience.

The shape of class-specific age-earnings profiles in Russia is quite different from the shape of British profiles reported by Goldthorpe and McKnight (2006). For all classes, average earnings do not vary considerably across age groups and younger male workers tend to earn somewhat more than older male workers. However, for both male and female professionals there is more variability in earnings than for manual classes and average earnings peak at an older age (for managers the Russian profiles are very specific). This confirms that the logic of the analysis by Goldthorpe and McKnight (2006) can be applied to Russia, although with some limitations imposed by the characteristics of the Russian labour market.

Chapter 5 explored class differences in mortality. Research on class inequality in health has a long tradition in Western Europe (Kunst et al., 1998; Mackenbach et al., 2008; Rose and Harrison, 2010). For Russia, the pattern and size of class inequality in mortality has not previously been studied.

I conducted a separate analysis of class mortality for men and women, with the estimates for men being more reliable because of a larger number of deaths. The results have shown that there is a manual vs. non-manual class gap in mortality in Russia, both for men and women. This is consistent with the previous results for Western countries. The manual vs. non-manual gap in mortality appears to be larger in Russia compared to Western European countries.

At a more detailed level of class analysis, the estimates are less reliable, especially for women, as the standard errors are large. However, for men an interesting pattern can be noticed. In contrast to Britain, there is not much difference in the mortality risks of higher and lower professionals. This may reflect a disadvantaged labour market experience for the Russian intelligentsia (higher professionals) during the market transition. Men in all manual classes (routine, lower technical, lower sales and service, lower supervisors) have similar mortality risks, although the mortality risks of the lower sales and service class are somewhat higher. However, again in contrast to Britain, unskilled routine and skilled lower technical workers have very similar mortality risks while it could be expected that the risks of skilled workers would be lower. This may be a consequence of the industrial crisis in post-Soviet Russia, as many skilled workers are employed in the industry, while most non-skilled workers are employed in the service sector and transport. Admittedly, these hypotheses remain tentative, as the power of the statistical analysis is limited due to a relatively small sample size.

There are also other results of the analysis of inequality in mortality in Russia, some of which are not directly related to class. First, there is no statistically significant difference in our sample in the mortality risks of workers in the state and in the private sectors of the economy. Second, mortality in Russia is associated with subjective status, even after controlling for occupational class, education and household income. There is a statistically significant partial correlation between mortality risks and subjective wealth for men and subjective respect for women. This may indicate different causal mechanisms that relate subjective status and health for men and women. Third, Russian men and women who were mobile in the labour market during the market transition have lower mortality risks. This effect is observed both for downward and upward class mobility.

There are two traditional approaches to measuring occupational inequality in the social stratification literature. One approach focuses on occupation-based social classes, while in the other researchers apply various types of occupational scales. In chapter 6 I constructed a relational occupational scale for Russia to see if the occupational hierarchy in Russia is different to that of Western countries. The results show that the Russian scale is well correlated with the scales constructed with the same methodology for Western countries. Professionals are at the top of the scale, followed by managers and then by occupations that require both non-manual and manual components of work. Manual occupations, in particular unskilled, are at the bottom of the scale.

The Russian scale is well correlated with the proportion of people with higher education in occupational groups (and to a lesser extent, with occupational income). As the scale was constructed on the basis of the analysis of intermarriages between occupational groups, this suggests a high degree of educational homogamy in Russia. The scale also correlates with the International Socio-Economic Index (ISEI), calculated with the cross-national data on occupational income and education.

Let us summarize the results. The analysis shows that the application of the international occupational class schema, the ESeC, is valid in Russia. The ESeC classes are correlated with validation variables in the theoretically expected way. Perhaps this is not very surprising. Industrial countries share some basic characteristics, and occupational hierarchy is one of them (Treiman, 1977). It would be hard to find a country where professionals have worse employment contracts and lower social standing than manual workers. In their paper, "A Normal Country", Shleifer and Treisman (2004) argue that in international comparisons post-Soviet Russia should not be perceived as some sort of an 'outlier'. It is a normal country both in terms of economic development and political institutions when compared with other middle-income countries, such as Turkey or Argentina. In terms of the structure of occupational inequality, Russia also is a normal country: there are simply not so many differences between Russia, EU countries and the USA.

This is not to say that everything is the same. The class structure in Russia is different than in developed Western European countries and has a higher proportion of manual classes, especially for men. Some specific characteristics of the labour market in Russia, such as high occupational mobility and low returns to work experience, affected the distribution of earnings across age groups in a way that is unusual for Western countries way. It is likely that class inequality in mortality also reflects specific Russian experience in the post-Soviet period.

As already noted above, in Russia, in contrast to Britain, there are not so many differences within non-manual and manual classes in respect to both mortality risks and economic security. Managers, higher and lower professionals seem to be more similar in Russia than in Britain, as well as skilled and unskilled manual workers, although the gap between manual and non-manual classes clearly exists and, at least for mortality risks, it is larger than in Europe. As the analysis in Chapter 4 showed, many labour market processes in Russia have been happening at the occupational and sectoral levels, which may explain relative homogeneity within both manual and non-manual classes. It is reasonable to attribute this feature to rapid structural changes in the Russian labour market since the collapse of the USSR. In future we may expect more differentiation between classes within the manual and non-manual groups of workers, although of course at the moment this claim cannot be supported empirically.

In the analysis presented in this thesis I separated managers, higher and lower professionals into three distinct classes. The original version of the ESeC keeps managers and professionals together and differentiates between higher managers and professionals and lower managers and professionals. There is a debate in the literature as to whether managers and professionals should be separated in the class analysis. Some argue that this would contradict the theoretical foundations of Goldthorpe's class scheme (McGovern et al., 2007), while others show that managers and professionals are clearly different in respect to some social outcomes (Gerber and Hout, 2004; Bian and Gerber, 2008).

The analysis for Russia shows that employment contracts of managers and professionals are indeed quite similar. There are no great differences between them in terms of the probability of informal employment, fringe benefits and unemployment risks. The mortality risks for these groups are also similar. This is evidence in support of combining managers and professionals into one or two classes, as is done in traditional class analysis. On the other hand, the age-earnings profiles of the two classes in Russia are clearly different, and it has previously been shown by Gerber and Hout that their earnings and intergenerational mobility patterns also differ. Professionals occupy a higher position on the relational occupational scale than managers, most likely because of their higher average education. The conclusion is that the decision about the separation of managers and professionals should be made according to the nature of the outcome variable of interest.

I conclude with two remarks that do not directly follow from the empirical results of the thesis, but refer to a broader question of the future of class analysis in sociology.

First, to date most of the empirical analysis based on occupational characteristics (either class or occupational scales) in sociology has been descriptive. This thesis is not an exception to this rule. The usual strategy is to conduct some kind of regression analysis where class (or other occupation-based measures) is an independent variable and the outcome variable of interest is a dependent variable, and to control for a number of possible confounders (sex, age, education, etc.). The problem arises when the results of this analysis are given causal interpretation. In most cases this interpretation is not correct. Two major problems are reverse causality and, to a larger extent, omitted variable bias.

There are many factors that are correlated with class and many outcome variables, and are not usually accounted for in regression equations. Modern evolutionary genetics and psychology suggest that many social outcomes are affected by genetic factors, and it is likely that genetic make-up is also correlated with class. This factor is usually impossible to control for. Other, non-genetic factors, such as unmeasured attitudes that affect both occupational choice and many outcomes, are also a likely source of potential omitted variable bias. Also, the usual strategy in the social sciences to control for variables that are themselves affected by class, introduces additional bias.

Perhaps one of the directions for the future development of class analysis is a more rigorous approach to the problem of causality. The counterfactual approach to causality (Rubin, 1974; Holland, 1986), now widely accepted in statistics and econometrics, offers a number of techniques for the identification of causal effects (instrumental variables, regression discontinuity, matching) (Angrist and Pischke, 2009) that can be usefully applied in research on social class. None of these techniques is a perfect solution to the problem of causal inference, and their application in social stratification research will face additional challenges. However, I believe that they show a way forward for the discipline of social stratification.

Second, in recent decades sociology has witnessed a debate among the proponents of the different types of occupation-based analysis. The current discussion seems to be conducted around several main points of view. For class analysis, Goldthorpe's class schema and its derivatives remain the most widely applied tool. Another empirical approach, advocated by Grusky and Weeden, is to use a more detailed occupational schema that captures inequalities at the level of separate occupations. Both sides use a number of theoretical arguments to justify their position (see a review in Goldthorpe, 2007b).

However, at the level of empirical analysis these approaches do not necessarily contradict each other. Clearly, some occupations are more similar to each other than to others, and aggregating them into larger classes may be a useful tool in empirical analysis, especially when the aggregation is performed in a theoretically informed way. On the other hand, it is hard to argue that there is high occupational heterogeneity within large occupational classes (as, for example, recent analysis of the effects of occupational class and occupational status by Chan and Goldthorpe suggests). For some analytical purposes, the use of separate occupations rather than large classes may be preferred, especially when the sample size allows us to do this.

Yet another approach is to use some kind of occupational scale (based on occupational income, occupational education, prestige, or ISEI and relational scales). An advantage of this approach is that it saves us degrees of freedom in statistical analysis, as in this case occupational hierarchy is measured on a continuous scale. A disadvantage is that the structure of occupational inequality becomes less clear. Perhaps this approach can be recommended when the task is to control for occupational characteristics rather than to focus on the effect of occupation or class.

In general, there are no particular reasons to believe that there is only one correct approach to measuring occupational inequality. All existing approaches can be applied, depending on the nature of the research enterprise.

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