LABOR MARKET SEGMENTATION:
THE CASE OF UKRAINE AND
RUSSIA

by

Stepanchuk Serhiy

A thesis submitted in partial fulfillment of
the requirements for the degree of

Master of Arts in Economics

National University of "Kyiv-Mohyla Academy"
Economics Education and Research Consortium
Master's Program in Economics

2003

Approved by ____
Ms.Svitlana Budagovska (Head of the State Examination Committee)

____

____

____

Program Authorized
to Offer Degree Master's Program in Economics, NaUKMA

Date ____

National University of "Kyiv-Mohyla Academy"

Abstract

LABOR MARKET
SEGMENTATION IN
TRANSITIONAL ECONOMIES

by Stepanchuk Serhiy

Head of the State Examination Committee: Ms.Svitlana Budagovska,
Economist, World Bank of Ukraine

This paper explores the issue of labor market segmentation in the transitional economies of Ukraine and Russia. It utilizes the switching regression analysis to test for the existence of two separate wage-setting mechanisms in these two labor markets, as predicted by the dual labor market hypothesis. The estimated results suggest that Ukrainian labor market is better explained in the terms of dual labor market model. At the same time, the results for Russia are more ambiguous, since the difference between the two segments is less pronounced. Recognizing that the switching regression results are equivalent to assuming some peculiar heteroscedastic distribution of the error term, the model is subjected to the goodness of fit test, and is compared to a single-equation specification which assumes complex heteroscedastic nature of the errors along the lines of predicting the actual wage distribution. Furthermore, the results are subjected to a sensitivity analysis, which suggests that they are robust to variations in model specification.

TABLE OF CONTENTS

Chapter 1. INTRODUCTION………………………………………………...1

Chapter 2. THEORETICAL FRAMEWORK…………………...…………..4

Chapter 3. ECONOMETRIC METHODOLOGY……….…………………16

Chapter 4. EMPIRICAL RESULTS…………………...……………………24

Data and Samples……………………………………………………...24

Model Specification………………………………………………….....25

Results for Ukrainian Sample…………………………………….…….27

Results for Russian Sample……………………………………………….34

Goodness of Fit Test ...……………………………………………………...40

Sensitivity Analysis……………………………………………….……45

Chapter 5. SUMMARY AND CONCLUSIONS……………..………...…...49

BIBLIOGRAPHY…...………………………………………………………..52

LIST OF FIGURES

Number *Page*

1. Hypothetical Scatter Plot – Standard Human Capital Theory …………...21

2. Hypothetical Scatter Plot – Dual Labor Market Theory ……………….....21

3. Frequency Distribution of Predicted Probabilities of Primary Sector Attachment, Ukrainian Sample………………………….....30

4. Distribution of Predicted Probabilities of Primary Labor Market Sector Attachment, Russian Sample………………………………………36

5. Actual and Predicted Wage Distribution, Ukrainian Sample…………….43

6. Actual and Predicted Wage Distribution, Russian Sample………………44

7. Distribution of Predicted Probabilities of Primary Sector Attachment, Ukrainian Sample (with Experience term included in the switching regression)……………………………………………46

8. Distribution of Predicted Probabilities of Primary Sector Attachment, Russian Sample (with Experience term included in the switching regression)……………………………………………47

LIST OF TABLES

Number *Page*

1. Switching Regression Model, Ukrainian Sample……………………..……..…..…………………………………27
2. Descriptive Statistics of the Primary Segment as Compared to the Total Sample, Ukrainian Sam…le…………………………………..….32
3. Composition of the Primary Segment as Compared to the Total Sample, Ukraine Sample…..……………………………………………32
4. Switching Regression Model, Russian Sample……………………….….35
5. Descriptive Statistics of the Primary Segment as Compared to the Total Sample, Russian Sample……………………………………….....37
6. Composition of the Primary Segment as Compared to the Total Sample, Russia……………………………………………………..…...38
7. Definition of Variables Used in Regression Analysis (Ukrainian Sample)…..52
8. Description of Variables Used in Regression Analysis (Russian Sample)…....53
9. Switching Regression Model, Controlling for Employer Size. Russian Sample……………………………………………………………….....54
10. Two-Step FGLS model (Ukrainian Sample)……………………………….55
11. Two-Step FGLS model (Russian Sample)…………………………….....56
12. Switching Regression Model (with Experience and Experience Squared Included in the Switching Equation), Ukrainian Sample……………....57
13. Switching Regression Model (with Experience and Experience Squared Included in the Switching Equation), Russian Sample………………...58
14. Switching Regression Results, Controlling for Geographical Regions, Ukrainian Sample…………………………………………………59
15. Switching Regression Model, Controlling for Geographical Regions, Russian Sample……………………………………………………..60

ACKNOWLEDGMENTS

I would like to express my sincere appreciation to my thesis advisor, Dr. Hartmut Lehmann, for his encouragement and guidance in the process of working on this research. I am also grateful to Dr. Tom Coupe for his patience and support, and Dr. Peter Kennedy and Dr. Kevin Lang for insightful conversations which provided me an invaluable help in the process of writing this research. Special thanks to Olexander Zhylevsky for his assistance in obtaining the data for the empirical analysis.

GLOSSARY

SLM -- Segmented Labor Market

Dual Labor Market Theory – assumes the existence of two separate labor market segments, primary and secondary; furthermore, primary sector, desirable jobs are assumed to be rationed

Chapter 1

INTRODUCTION

The process of economic transition in the countries of former Soviet block has been accompanied by dramatic socio-economic shocks faced by the people in these societies. Definitely, one of the most noticeable among them has been the rapid changes in the income and wage structure in these countries. Once centrally determined according to administratively set wage grids, it was let to be settled by the market forces of supply and demand. This was accompanied by a large increase in overall income inequality and creation of a huge class of low-earners. As is vividly described in Commander at al. (1999), one of the most popular images of the transition process is that it has brought "apparently rapid transformation of an entire system from one characterized by low inequality and largely absent poverty to one marked by extremes of deprivation and prosperity".

It is documented that one of the main driving forces behind the growing income inequality has been the increase in wage dispersion. Milanovic (1998) notes that "the most important factor driving inequality upwards was increased inequality of wage distribution". Similarly, Garner and Terrell (1998) find that in Slovakia, "changes in the distribution of non-agricultural earnings explain the lion's share of the increase in overall inequality." Finally, Brainerd (1998), who investigated the changes in wage distribution in Russia concludes that "the transition to a market economy has produced a substantial and rapid change in the wage structure in Russia… Overall wage inequality nearly doubled from 1991 to 1994 and has reached a level higher than that in the United States".

The issues of growing wage and income dispersion and the creation of a large class of low-earners has proven to be highly pertinent for transition economies, as the failures to take a proper account of them often aroused social tensions, leading to slowdowns or even setbacks in the reforms. This naturally calls for a careful study of factors and mechanisms that lie behind these processes.

Standard human capital theory postulates that individual's wages are mainly determined by his or her productive ability, and that individuals who find themselves in low-wage jobs are low-productivity workers either unwilling or unable to obtain the skills necessary to move to a more desirable job. However, casual observation of the reality suggests that in the post-soviet transitional economies, for many their labor market outcomes are only weakly, if at all, related to their education and experience – the factors, which, as human capital theory holds, are the main determinants of the person's productive ability.

Labor market segmentation theory emerged largely as a response to such pervasive social problems as the persistence of poverty and income inequality, and inability of low-earners to move up the social ladder. Noticing the inability of the standard neoclassical theories to explain these phenomena, it proposed an alternative and intuitively appealing view of the labor markets. The implications of this theory are also in stark contrast to those of the standard neoclassical theories of labor markets. The latter stress the importance of promoting education and obtaining skills among the low-earners, while the former argues that primary-sector, desirable jobs are rationed, stressing the creation of primary jobs, and ensuring a fair treatment of certain "disadvantaged" groups of workers which have high chances to be confined to the secondary-sector jobs.

This thesis is an attempt to assess the validity of the segmented labor market views of the labor markets in the two transitional economies of Ukraine and Russia. For the empirical test of the dual labor market hypothesis, we use the switching regression method developed in this context by Dickens and Lang (1985). We assess whether the dual labor market theory provides a more appropriate account of the current situation in labor markets in these two countries. To counter a popular criticism of the switching regression approach, we compare our model to the single labor market specification which allows for complex heteroscedastic nature of the error term, and test whether our model provides a better description of the actual wage distribution.

The remainder of the thesis is organized as follows. In chapter 2 we introduce theoretical framework for our empirical model. Chapter 3 elaborates on the econometric details of the switching regression analysis used in this paper. The following chapter presents the results from our empirical analysis. Finally, we summarize our findings and draw some conclusions.

Chapter 2

THEORETICAL FRAMEWORK

The early works on labor market segmentation are often traced back to the institutionalist and radical economists. The theory of segmented labor markets (subsequently referred to as SLM theory) was formalized in the late 1960-ies and early 1970-ies, among others in the works of Piore and Doeringer, mainly as a response to such widespread social phenomena as the persistence of poverty and income inequality. As Michael J. Piore vividly explains, to SLM theorists "the problem of poverty could be best understood in terms of dual labor market… The poor are confined to the secondary labor market. Eliminating poverty requires that they gain access to primary employment" (Piore, 1970).

Although SLM theories provided an intuitively appealing description of the labor markets (according to Vietorisz and Harrison (1973), "there are good jobs and there are bad jobs. This is such a commonplace fact of life that it often goes unquestioned"), their authors often diverged from the standard methods of analysis recognized as appropriate by the neoclassical paradigm. For this reason, the early works on labor market segmentation were dubbed as "dissident theories of the labor market"(Cain, 1976). The critics of the early SLM writers viewed them as atheoretical. Moreover, their empirical conclusions were often based on questionable statistical analysis, which used the methods (such as, for example, interviews and observational studies) that were incompatible with the standard econometric techniques adopted by the mainstream economists.

However, over the course of time, many of the SLM ideas were successfully integrated into the neoclassical apparatus. Rebitzer (1993) notes that "on many microeconomic issues, the clear line that once distinguished radical political economists' accounts of labor market segmentation has been blurred" and that "so many of the microeconomic issues raised by the radical political economy literature have been absorbed so thoroughly into (and often improved by) the mainstream of the economics profession that it is often impossible to distinguish one body of work from the other".

Recently, there has been a revival of the interest to SLM theories among the mainstream economists. According to Dickens and Lang (1988), "the (SLM) theory has been pursued by economists using modern tools of imperfect information and state-of-the-art econometrics".

Rebitzer argues that SLM theory challenges the conventional microeconomic view of the labor market, according to which "workers with identical productive abilities should, in the long run, be paid the same wage". This conjecture is a version of the "law of one price", which states that identical commodities should sell for the same price in a competitive market, and any short-run deviation from this equilibrium should be eliminated as the buyers switch from the more expensive goods to their cheaper equivalents. However, the SLM theory postulates that this will not be the case in labor markets, even in the long run. The SLM view is that "long-run equilibrium in labor markets will be characterized by rationing of high wage, desirable jobs. As a result of this rationing, workers able and willing to accept desirable jobs at going wages will be stuck in less desirable jobs – perhaps for long periods of time" (Rebitzer, 1993).

Although it is possible (and perhaps highly probable) that there exist several different labor market segments, it is conceptually useful to simplify the analysis by assuming the existence of the two separate labor market segments. The essence of this dual labor market hypothesis is summarized in Dickens and Lang (1988): "labor market can be usefully described as consisting of two sectors: a high-wage (primary) sector with good working conditions, stable employment, and substantial returns to human capital variables such as education and experience, and a low-wage (secondary) sector with the opposite characteristics. Moreover, primary jobs are rationed, that is, not all workers who are qualified for primary sector jobs and desire one can obtain one."

Dickens and Lang further argue that "segmented labor market models are simultaneously a description of the income distribution, a claim about the absence of market clearing, and a radical departure from the standard neoclassical assumption of fully rational actors and exogenously determined preferences". The last of these claims deserves some further explanation. According to Dickens and Lang, "the sector of the labor market in which the individual is employed directly influences his or her tastes, behavior patterns, and cognitive abilities". As is further articulated by Rebitzer, "primary workers who work for employers that reward stable behavior, will as a result develop attitudes toward a job that encourage stability. Conversely, secondary workers will develop attitudes that encourage instability". These "ingrained" or endogenously developed attitudes towards non-pecuniary characteristics of the job will make it more difficult to move from the job in the secondary sector to the one in the primary.

The segmented labor market theory is often viewed as an alternative to the neoclassical human capital theory, which "emphasize differences among people, rather than among jobs, as a determinant of a distribution of income" (Dickens and Lang, 1985). The direct consequence of this theory is that "workers in low-wage jobs are viewed simply as low-productivity workers who are unwilling or unable to obtain the skills that are necessary for access to higher paying jobs", and the main way to eliminate poverty is "to provide individuals with more skills, or with incentives to obtain skills". At the same time, Bulow and Summers (1986) point to the fact that existing studies "consistently find that differences in genes, parental upbringing, years of schooling and IQ all taken together can explain only a very small part of inequality of wages" (they site as an example the studies of identical twins by Jencks (1972) and Taubman (1977), who find that "expected absolute difference in earnings between identical twins is about two thirds as great as between randomly chosen members of the population"). Jencks (1972) and Thurow (1976) attribute this fact to possible importance of luck in wage determination. The models of the dual labor market presented below will offer some explanation of how luck can affect wages in competitive markets.

Rebitzer and Taylor (1991) argue that one of the most important differences distinguishing dual labor market theory from such alternative explanations of wage distribution as human capital theory and the theory of compensating wage differentials is the nature of the labor market equilibrium – according to dual labor market theory "equilibrium is characterized by an excess supply of qualified workers to primary jobs. Mobility between secondary and primary jobs will therefore be limited, and "good" workers may be stuck in "bad" jobs".

Segmented labor market theorists further argue that, since the primary sector jobs are rationed, training programs will not succeed in eliminating poverty, and that "the major roles for policy are providing income support, ensuring that the rationing system is "fair" and minimizing the extend of the secondary sector by stabilizing aggregate demand" (Dickens and Lang, 1985).

It is obvious that for the above-described segmentation to exist, there must be some reasons why firms in the primary sector would be willing to pay persistently higher wages to their employees, instead of hiring outside labor at a market-clearing wage. Several alternative explanations of this phenomenon have been proposed. Most of them are direct extensions of the efficiency-wage theories, which are summarized in Yellen (1984). The basic assumption of these models, as formulated in Solow (1979), is that the output of the firm is a function of both the number of employees and the effort per worker, which in turn positively depends of the real wage:

$$Q = F(e(w)N) \qquad (1)$$

where N is the number of workers employed, e is the effort per worker, and w is the real wage rate. The idea that workers' efforts positively depend on wages goes back at least to Adam Smith who observed that "the wages of labor are the encouragement of labor which like every other human quality improves in proportion to the encouragement it receives: where wages are high accordingly we shall always find the workmen more active, diligent and expeditious than when they are low".

Solow shows that profit-maximizing firm will offer a real wage w* (known as the efficiency wage) which satisfies the condition that the elasticity of effort with respect to the wage is 1. Some workers would prefer to work for the wage lower than w*, but the firm will not hire them at lower wages, since such reduction in wages would lower the effort, and hence the productivity of all the firm's workers. Yellen argues that "dual labor markets can be explained by the assumption that the wage-productivity nexus is important in some sectors of the economy, but not in others. For the primary sector, where the efficiency-wage hypothesis is relevant, we find job rationing and voluntary payment by firms of wages in excess of market clearing; in the secondary sector, where the wage-productivity relationship is weak or nonexistent, we should observe fully neoclassical behavior".

Bulow and Summers (1986) use the efficiency-wage idea to construct a model of the dual labor market. It parallels the model of involuntary unemployment of Shapiro and Stiglitz (1984), and is based on employers' need to motivate workers. The central assumption of their model is that firms' ability to measure workers' efforts is imperfect in the primary sector because of the "responsible character of the primary-sector jobs", while secondary-sector jobs are "menial" and easy to monitor. As a result, secondary-sector workers receive a wage which is equal to their marginal product $w(s) = \hat{w}$. Since the monitoring of workers in the primary sector is difficult, both "false positives and false negatives may result as firms try to detect shirkers". Thus, workers who do not shirk have some instantaneous probability d1 of being falsely labeled as a shirker, and those who shirk have the instantaneous probability d2 of being identified as a shirker. Hence, the probability of being labeled as a shirker over the increment of time is $(d_2 - d_1)dt$ greater for those who are shirking as compared to non-shirkers. It is further assumed that there exists some exogenous separation rate q (which may occur either because of worker quits to reallocate or withdraw from the labor force, or are induced by employer because of changes in product demand), and that shirking adds an instantaneous gain to worker's utility equal to α1. Only two levels of effort are possible in the model, and shirking workers are assumed to produce no output. Using these assumptions, the authors conclude that the workers in the primary sector will not shirk only if the following condition is satisfied:

$$\alpha \le (d_2 - d_1)(PV_1 - PV_2) \qquad (2)$$

where PV1 and PV2 denote the present value of lifetime utility for workers in the primary and secondary sectors, respectively. The left-hand side of this formula represents an instantaneous gain of utility from shirking, and the right-hand side is a product of incremental probability of being fired because of shirking and the loss in lifetime utility if fired from the primary-sector job.

---

[1] They assume N identical infinitely lived agents whose utility may be represented by $U = \int_t^\infty U(x_1, x_2 + \alpha s)e^{-r(v-t)}dv$, where x_i number of units of sector *i* consumed in period *t*, *s* is the indicator variable equal to 1 if the worker shirks and 0 otherwise, and *r* is the discount rate.

Having calculated the present values of lifetime consumption in the two sectors from two recursive equations, the authors obtain the no-shirking condition for the primary sector wages:

$$w_1 - \hat{w} = \frac{\alpha r}{d_2 - d_1} + \frac{\alpha(d_1 + q)N}{(d_2 - d_1)(N - E_1)} \qquad (3)$$

where N is to total number of workers, and E1 is the number of workers employed in the primary sector. This relation implies that the wages the primary-sector firms have to pay to ensure that their workers do not shirk increase with an increase in utility from shirking α, the rate of turnover among non-shirkers d1+q, discount rate r and the number of primary sector jobs E_1.

This model predicts that "in any economy in which firms cannot monitor workers perfectly, they will pursue policies that will cause workers to value their jobs". As a consequence, there will exist wage differentials not related to skill differentials. It follows that even though the workers are identical, in equilibrium primary-sector wages will exceed secondary-sector wages. Bulow and Summers argue that "workers in the secondary sector will envy those in the primary sector, but it will not be possible for them to bid for the primary-sector jobs by being willing to accept lower wages. For if they accepted lower wages, they would have an incentive to shirk. Hence firms will not offer lower wages".

Rebitzer and Taylor (1991) further develop the ideas of Bulow and Summers and show that, if firms face uncertainty in product demand, dual labor market can arise even if there is no difference in monitoring costs in the primary and secondary sector. In their model, the uncertainty is represented as follows: in each period firm's revenue is equal to θf(L), where θ is the product price, which is "a random draw from a known distribution". Rebitzer and Taylor shows that profit-maximizing firm may find it profitable to offer both primary and secondary jobs, that wages paid to primary workers will exceed the wages of secondary (contingent) workers, and that there will be an excess supply of workers to the primary jobs.

The above-described models of dual labor market follow neoclassical tradition of assuming "individualistic maximization by all agents" (Yellen, 1984). Another strand of the SLM literature provides sociological explanations of the existence of the two separate labor market segments. This tradition goes back at least to Michael J. Piore, who writes: "At the core of labor market segmentation are social groups and institutions. To understand these phenomena, one therefore needs a paradigm which recognizes and encompasses social, as opposed to individual, phenomena" (Piore, 1983). Similarly, Solow (1980) argued that wage rigidity, which is the base of the efficiency-wage models and SLM theories, may "more plausibly be caused by social conventions and principles of appropriate behavior that are not entirely individualistic in origin".

The first formal model which emphasized sociological aspects of labor market segmentation was provided by Akerlof (1982). He views the worker-employer relations as a "partial gift exchange", arguing that workers' effort depends upon the norms determining "a fair day's work" which evolve within the working group and thus are social by their nature. These norms are, at least partially, determined by, and at the same time influence the wages paid by the firm. According to Akerlof, "the gift of the firm to the worker (in return for the worker's gift of hard work for the firm) consists in part of a wage that is fair in terms of the norms of this gift giving". Akerlof shows that, contrary to neoclassical models of the labor market, it may be advantageous for the firm to pay a wage in excess of the minimum at which it can acquire labor in attempt to influence the norms of the working group, and hence the effort of the workers. Akerlof states that where such "interior solution" occurs, the labor market is primary, while if the "boundary solution occurs, the labor market clears; the market is secondary". He further argues that "a worker entering the primary labor market will not automatically find work at the wage received by equally qualified employed persons". In contrast, a worker in the secondary segment can readily obtain work at the wage received by workers of similar qualifications.

Great attention in the SLM literature is placed on the issue of discrimination in the labor market. As Cain (1976) notes, "the large and persistent differentials in earnings and wages between white and black males and between males and females – even when productivity indicators are apparently equal – do, indeed, present a challenge to orthodox theory". Standard competition assumptions of the neoclassical model predict that such discrimination should be eliminated in the long run. Firms that did not discriminate would have lower costs and grow, thus forcing those firms that adopt discriminatory practices to leave the market, thereby eliminating discrimination. In the process, the demand for equally qualified workers from the discriminated group would increase, tending to equalize the wages between the two groups of workers.

It is possible that firms will persistently engage in discriminatory practices, if the "ascriptive characteristics" of different groups of workers are expected to be correlated with "unobservable characteristics that determine the effectiveness of the incentives used by employer (such as, for example, expected tenure or preferred hours of work)" (Rebitzer, 1993). Since primary employers naturally prefer workers having long expected tenure (as expected utility of any "employment rent" or wage premium in the primary sector over that in the secondary sector increases the longer an employee expects to remain with the firm), but typically lack direct information about the expected tenure of their workers, they "may engage in statistical discrimination against women if women, as a group, have shorter expected tenure than their male counterparts".

This idea is reflected in the Bulow and Summers paper (1986). They show that, if there are two distinct groups of workers with different separation rate (for example, women having higher separation rate than men), the group with the shorter horizons in the primary-sector job will require higher wages in order to induce them not to shirk. As a result, the chance of finding a job in the primary sector will be lower for this group than for the group with longer job horizons. This proposition may account for the fact that, as noted in Bulow and Summers, "marriage raises the wages of men but reduces or has no effect on the earnings of women". The reason behind this is that marriage probably increases the costs of losing a good job for men, while it may reduce the cost to women. As a result, it reduces the probability of employment separation among men, but increases it among women.

Another possible explanation of the discriminative practices is proposed by the "divide and rule" models of Roemer (1979), Bowles (1985) and Gintis (1976), according to which "employers can reduce worker solidarity by treating one group of workers better than the other, equally productive group, which, in turn, would allow them to pay lower wages and/or extract more effort from their employees". (see Rebitzer, 1993).

Surprisingly, labor market segmentation received only limited attention by the researchers of labor markets in transitional economies, even though a number of studies point to high likelihood of its existence. The only direct test of the SLM theories in transition countries context is Lehmann and Luke (2001), who study the issues of labor market segmentation in Estonia. They use the methodology developed in Dickens and Lang (1985), which will be discussed below. Their results suggest some (although not conclusive) support to the SLM hypothesis, allowing them to conclude that, as Estonia progresses in its transition, its labor market seems to increasingly resemble the picture drawn by the SLM theorists.

An interesting finding is that “most workers in Estonia seem to belong in the secondary labor market, where remuneration and working conditions are poor and only a relatively small group of workers find themselves in the primary labor market”.

Grosfeld et al. (1999) claim that Russian labor market is characterized by puzzling coexistence of the elements of inertia, such as pervasive labor hoarding and importance of social assets owned by the firms, and dynamism, as witnessed by high mobility of some workers. They develop a model which is called to explain these divergent tendencies. According to their model, the Russian labor market is divided into a stagnant pool of less productive workers who accept the low wage offers with the access to the social services provided by their firm, and a dynamic segment of more productive workers, who have better employment perspectives and choose to contract on the spot labor market. The authors suggest that this leads to ex post labor market segmentation, in which the more productive workers are concentrated in firms with relatively good performance. They claim to find empirical confirmation to their hypothesis. However, their findings are based on the assumption that blue collar workers are the most demanded employees, while white collar workers are the less adapted to the new market environment. Thus, in their regression analysis, they approximate the more productive and less productive workers as white collar and blue-collar workers, respectively. Although there may be some elements of truth in this assertion, it is highly unlikely that it accurately reflects the whole true picture of the transitional labor market. Indeed, both white-collar and blue-collar workers may be expected to constitute highly heterogeneous groups, with varying labor market experience.

Koumakhov and Najman (2001) conclude that there are some “distinct signs of the segmentation of employees”, but note that “this segmentation is not reduced to conventional division blue collars vs. white collars or low skills vs. high skills”.

Boeri and Flinn (1999) analyse the labor mobility in Poland, and comes to conclusion that its labor market may be segmented in the sense that there is "a significant degree of segmentation in the allocation of job offers between the public and private sectors". Their empirical findings seem to support their claim of limited workers' mobility between these two sectors. Although the division of the labor markets into the public and private sectors may be useful, it also may fail to capture some important features of the labor markets of the transitional economies, and more fundamental approach to the analysis of the labor market segmentation in these countries, without a prior "ad hoc" definition of the segments, may prove to be useful.

Chapter 3

ECONOMETRIC METHODOLOGY

As was discussed in the previous section, SLM theory predicts that labor market outcomes for low-income or marginal workers are different from those for high-income earners. Thus, it is tempting to fit a traditional human capital regression to the sub-sample of low-wage earners and test whether the estimated results show positive returns to education and experience, and whether they are significantly different from those of high-wage earners. This was the approach used in early attempts to test the SLM theory (for example, Doeringer et al., 1972, Osterman, 1975, Harrison, 1972). Cain (1976) shows that this approach is seriously flawed, since it effectively truncates the dependent variable for the low-earners sub-sample from above, and hence, the estimated coefficients are biased downwards. Thus, finding distinct wage equations for high-wage and low-wage earners would be a purely statistical artifact.

Heckman and Hotz (1986) correct the bias by using the sample selection techniques in their study of the Panamian labor market. They divide their sample into two sub-samples using the poverty line as a threshold, and test whether a selection bias corrected earnings function fitted to the non-poor sector correctly predicts the earnings of the poor. Their results support the dual labor market hypothesis for Panama. At the same time, they note that their results assume that poverty status allows one to perfectly classify the observations into either primary or secondary segments.

Dickens and Lang (1992) argue that it is difficult to determine a priori who is in which sector, since there may be both primary and secondary sector workers even within the same firm, and hence, it is appropriate to treat sectors as unknown.

These two authors pioneered the usage of the switching regression technique in the context of testing the dual labor market hypothesis (Dickens and Lang, 1985). They argue that this method allows one to avoid both the selectivity bias, and circumvent the problem of circular definitions of the sectors.

The switching regression methodology is thoroughly described in Goldfeld and Quandt (1976) and in Maddala (1986).

In our context, it is assumed that there are two distinct wage regimes – for the primary and secondary segments of the labor market. Although it is theoretically possible to introduce more than two separate wage regimes, the assumption of duality greatly simplifies the empirical analysis. As a result, the regression model consists of the following three equations:

$$Y_{i1}=X'_{i1}\beta_1+u_{i1} \qquad (4a)$$
$$Y_{i2}=X'_{i2}\beta_2+u_{i2} \qquad (4b)$$
$$Y^*_{i3}=Z'_{i}\gamma+u_{i3} \qquad (4c)$$

The first two equations describe the individuals' wages if in the primary or secondary sector, respectively, and the third, or "switching" equation allocates workers to these two wage regimes. Rebitzer and Robinson (1991) explain that the third, switching equation "can be understood as describing the ability of an individual to obtain a job in either the primary or secondary labor market", and hence should include among its dependent variables only those that measure the personal characteristics of individuals, and not the characteristics of the job. The Y_{ij}-s (j=1,2) are natural logarithms of individuals' wages in the two sectors. It is not known a priori to which regime the individual belongs, and thus, the Y_{i1} and Y_{i2} are non-observable. Instead, one observe Y_i-s, which are classified according to the following rule:

$$Y_i = Y_{i1} \text{ if } Y^*_{i3} \geq 0 \text{ (or if } u_{i3} \geq -Z_i\gamma) \qquad (5a)$$
$$Y_i = Y_{i2} \text{ if } Y^*_{i3} < 0 \text{ (or if } u_{i3} < -Z_i\gamma) \qquad (5b)$$

The Y^*_{i3}–s are also latent non-observable latent variables determined by the set Z of regressors (whose choice is described above), which may be completely different, or may have some variables in common with the X – the vector of the explanatory variables determining the wage within each sector. The two wage equations for the two labor market segments are usual Mincer-type wage equations. β_1 , β_2 and γ are the parameter vectors to be estimated, given observations on Z and X.

To complete the model specification, some assumptions are needed concerning the distribution of the three error terms (u_1, u_2, u_3). In practice, it is often assumed that they are jointly normally distributed with mean vector 0, and the covariance matrix

$$\Sigma = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & \sigma_2^2 & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & 1 \end{pmatrix}, \qquad (6)$$

where $\sigma^2_3=1$ is required for the identification purposes. For our estimation purposes, we adopt the model with exogenous switching, which means assuming that $\sigma_{13}= \sigma_{23}=0$.

Hartley (1978) demonstrates that with the above-stated assumptions, the pdf of the latent variables Y_1 , Y_2 and Y^*_3 is given by

$$g(Y_{i1}, Y_{i2}, Y_{i3}) = \prod_{i=1}^{3} f_i(Y_i), \qquad (7)$$

where $f_j(Y_i) = \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left[-\frac{1}{2\sigma_j^2}(Y_i - X'_{ij}\beta_j)^2\right], j = 1,2,3$ (8)

whereas the pdf of the observed dependent variable Y is

$$h(Y_i) = \Theta_i f_1(Y_i) + (1-\Theta_i) f_2(Y_i) \qquad (9)$$

with $\Theta_i = \Pr(Y_{i3}^* \leq 0) = \int_{-\infty}^{-Z\gamma} \phi(u)du = 1 - \Phi(-Z_i\gamma)$ - standard normal cdf. (10)

This produces the log-likelihood function of the form:

$$L(\beta_1, \beta_2, \gamma, \sigma_1^2, \sigma_2^2) = \sum \log\left[\Theta f_1(Y) + (1-\Theta) f_2(Y)\right] \qquad (10)$$

The log-likelihood function is solved through the EM algorithm of Dempster, Laird and Rubin (1977), as further developed by Hartley (1978)[2]. The estimation procedure uses the weights constructed as follows:

$$\begin{aligned} w_{i1} &\equiv w_1(Y_i) = \theta_i(f_1(Y_i)/h(Y_i)) \\ w_{i2} &\equiv w_2(Y_i) = (1-\theta_i)(f_2(Y_i)/h(Y_i)) \end{aligned} \qquad (11)$$

This algorithm estimates the classification vector, i.e. the vector of probabilities that a given observation belongs to one of the wage regimes, and then uses the

[2] The program to carry out the maximization in the Stata statistical package was developed by Frederick Zimmerman, Department of Health Services, University of Washington.

weights constructed as described above to estimate the parameters in each of the two wage equations. The residuals obtained from the two regressions are used to update the classification vector. Iteratively, this procedure converges to the maximum likelihood estimates of the parameters in the three constituent regressions. To start off the algorithm, it is necessary to assign the initial "guess" values to the classification vector.

Hartley (1978) notes that "limited Monte Carlo experiments with this algorithm indicate that convergence to a solution of the likelihood equation corresponding to a local maximum of L always obtains", and that "point estimates are very close to the true parameter values".

However, since the likelihood surface is not globally concave, several local maxima are possible. Hartley argues that this feature is shared by most other (local optimization) algorithms and "suggests experimentation with different starting values. If multiple solutions result, presumably the root which maximizes L is the consistent one". Hence, in our estimation, we tried several different initial classification vectors, and chose the results which produced the largest value of log-likelihood.

Since the single-equation specification is nested in the switching model, it is possible to test the hypothesis that the two-equation model fits the data significantly better than the single-equation model, using the LR test. However, as noted by Dickens as Lang (1985), several complications with this test arise. First, when the switching equation specification is constrained to yield the single-equation model, several parameters become unidentified, which complicates the calculation of the degrees of freedom. Furthermore, it is possible that the test-statistics does not have the asymptotic chi-squared limiting distribution. However, as was demonstrated by Monte Carlo simulations in Goldfeld and Quandt (1976), setting the degrees of freedom equal to the number of constraints plus the number of unidentified parameters gives a conservative test using the chi-squared distribution.

Having estimated the regression parameters, it is possible to examine if the results of the switching regression conform to the predictions of the SLM theory. Mainly because of the manual nature of the secondary-sector jobs, one would expect returns to the "human capital" variables such as education to be flat, or at least significantly lower in the secondary sector, as compared to the primary sector. This is illustrated on the following graphs (adapted from Dickens and Lang, 1985):

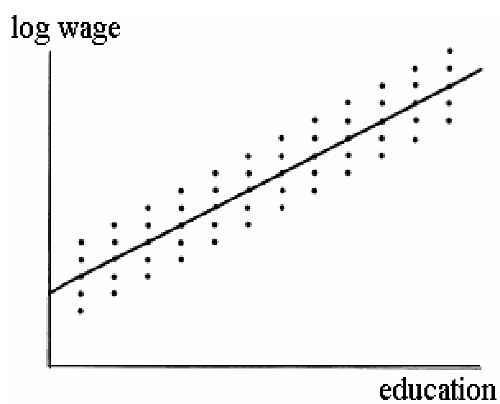

Figure 1. Hypothetical Scatter Plot – Standard Human Capital Theory

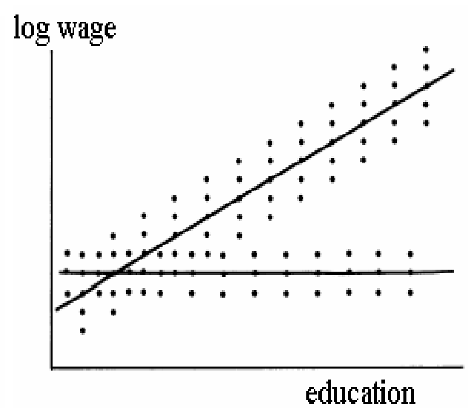

Figure 2. Hypothetical Scatter Plot – Dual Labor Market Theory

Dickens and Lang argue that if the person's earning potential could be summarized by a single trait – for example, education, as in this case, and an unobserved trait uncorrelated with education, than the standard view of the labor market would predict the relation between education and log wages as in figure 1, while that of the dual labor market theory would expect a scatter diagram similar to the one in figure 2. Intuitively, the essence of the formal statistical test described above is to see whether the two wage equations fit the data significantly better than one, and whether the best-fitting equations correspond to the predictions of the dual labor market theory.

As was already noted, the switching regression method in the context of dual labor market theory was initially used in Dickens and Lang (1985) and allowed them to corroborate the dual market hypothesis for the American labor market.

This technique was also utilized in Rebitzer and Robinson (1991), who tested whether there is an effect of the employer size on workers' wages. Theoretical support for this hypothesis comes from Bulow and Summers (1986), who showed that, if the probability of detecting a shirker is not given exogenously, but depends on the amount of resources spent on shirkers' detection, and if these resources are consumed according to the function $\phi(d_2)$ (where d_2 is the probability of loosing a job if caught shirking for the worker who shirks in the primary-sector job), the primary-sector firms will be solving the following problem:

$$min: w + \phi(d_2) \tag{12}$$

subject to no-shirking condition to produce the output most efficiently. Bulow and Summers further argue that large firms probably have less favorable $\phi(d_2)$ because of their size, and therefore substitute higher wage for supervision. Rebitzer and Robinson's empirical results support the dual labor market hypothesis. They also show that employer-size effect is indeed larger in the primary sector.

Switching regression technique was also used in Barsh and Paredes-Molina (1996) who test the dual labor market hypothesis in Chile, and in Vakis et al. (2001), who investigates the failures of the Peruvian labor market.

It was also used in Lehmann and Luke (2001) in their study of labor market segmentation in Estonia over the decade of transition.

Chapter 4

EMPIRICAL RESULTS

This section presents the results of econometric test of the dual labor market hypothesis in the two transitional economies of Ukraine and Russia.

Data and Samples

For the empirical analysis, we used the data from two sources. For Ukraine, the data come from the "The Survey on Households' Standards of Living" conducted by the Ukrainian State Committee of Statistics (Derzhkomstat) in 2000. It contains information on 25,133 individuals, and includes the data on various personal social and economic characteristics, such as age, gender, marital status, educational attainment, years of schooling, years of working experience, type of employment, enterprise ownership, region and place of living (city, town, or rural area), and annual income from various sources (separate categories for income from primary job, secondary job, self-employment, entrepreneurial activity, stipends, pensions etc.).

The Russian data come from the Russian Longitudinal Monitoring Survey (RLMS), which is conducted according to the World Bank's methodology of Living Standards Measurement Surveys by the Carolina Population Center, the University of North Carolina, and particularly from the Round X conducted in the year 2001. The original data file covers 10098 individuals, providing a detailed information on their education, job, earnings, and other characteristics.

We limited our analysis to males of prime working age (between 20 and 65 years old), who reported themselves as being employed and receiving positive earnings from their primary employment during the sampling period. This approach is conventional in the literature on labor market segmentation. Dickens and Lang (1992) explain that the reason for limiting one's attention to men only is "substantially different nature of many women's jobs and the difficulty of fitting them into the dual market typology [as] pink collar-jobs have many characteristics of both primary and secondary jobs". Further, we deleted observations for which information on some of the key variables, such as the level of education or working experience was missing. As a result, our cleaned samples comprised 3586 observations for Ukraine, and 1661 observations for Russia.

Model Specification

There does not exist a unanimous agreement as to which variables should be included in the wage equations and in the switching equation. However, as was discussed in the previous section, since the switching equation describes person's chances to be in the primary sector, it should include only his or her personal characteristics, and should not include any variables describing the workplace. The equations that determine the wages in both sectors are usual Mincer-type wage equations. They contain such usual "human capital" variables as educational achievement and working experience.

Contrary to Dickens and Lang (1985) who assumed constant returns to a year of schooling, we follow Lehamann and Luke (2001) and use the extended specification of the wage equations in the two wage regimes by including dummy variables for the highest level of educational attainment. We believe that this approach is more appropriate for the "parallel" nature of the Ukrainian and Russian educational systems, when different educational "certificates" may bare different value in the labor market, even if it requires equal time to obtain either of them. Some justification for this approach is provided in Boeri and Terrell (2001), who conclude that "there are significant differences in the "marketability" of the different types of education". For instance, vocational training, which was very popular and widespread in the past, often producing specialists with narrow skills for a particular enterprise, turned out to be not highly rewarded by the market mechanism. At the same time, there is a growing popularity of general secondary and tertiary education.

In our model, we included dummy variables corresponding to four different educational attainment levels – *high* standing for the university education, *ssec* for the specialized secondary (technical or medical) education, *voc* for vocational training, and *csec* for general secondary education, with individuals having only basic secondary (which is compulsory both in Ukraine and Russia) or lower education as a base category.

Further, we controlled for living in the capital city of Kyiv, and living in a town. Similarly, we included dummy variables for state and foreign enterprise ownership. Usually, investigators of the dual labor market in western economies (e.g. Dickens and Lang, 1985) focus their attention only to the private sector and exclude employees of the state-owned enterprises from their analysis. However, in transitional countries, such as Ukraine and Russia, there is a traditionally huge state sector inherited from the Soviet times, which continues to play an important role in the labor market. For instance, in the Ukrainian sample, 1523 observations (or 42.47 percent of the sample) represent employees of the state-owned enterprises. Thus, excluding employees of the state sector would significantly reduce our samples, and most probably limit one's ability to draw well-grounded conclusions which would pertain to the whole labor market. Instead, we included the *state* dummy variable for the employees of the state sector to control for possible differences in wage structures between the private and state sectors. For similar reasons, we included a dummy variable for the employees of the foreign-owned enterprises (including joint ventures), with domestic non-state firms being a base category. A detailed description of the variables included in the regression analysis for both Ukrainian and Russian samples are given in Appendix A (Tables 7 and 8).

Results for Ukrainian Sample

The estimated results from fitting the switching-regression model to the Ukrainian sample are presented below.

Table 1. Switching Regression Model, Ukrainian Sample
Dependent Variable: Log of Wages

Variable	***OLS***	***Primary***	***Second***	***Switching Reg***
high	0.607 (0.000)	0.506 (0.000)	0.281 (0.021)	0.777 (0.000)
ssec	0.394 (0.000)	0.362 (0.000)	0.247 (0.030)	0.328 (0.000)
voc	0.178 (0.016)	0.323 (0.000)	0.081 (0.449)	0.022 (0.481)
csec	0.057 (0.439)	0.149 (0.002)	-0.258 (0.015)	0.254 (0.000)
exp	-0.007 (0.059)	-0.005 (0.084)	0.0001 (0.972)	
exp_sq	-0.0001 (0.278)	-0.005 (0.244)	-0.0002 (0.012)	
state	0.241 (0.000)	-0.082 (0.000)	0.962 (0.000)	
foreign	0.744 (0.000)	0.296 (0.001)	1.878 (0.000)	
prop_un[3]	-1.077 (0.000)	-1.180 (0.000)	-0.653 (0.000)	
kyiv	0.588 (0.000)	0.423 (0.000)	0.201 (0.371)	0.948 (0.000)
urban	0.924 (0.000)	0.471 (0.000)	0.199 (0.001)	1.228 (0.000)
mar	0.216 (0.000)	0.305 (0.000)	0.078 (0.365)	-0.117 (0.000)
const	6.074 (0.000)	6.783 (0.000)	5.661 (0.000)	-0.544 (0.000)
St Error	0.988	0.580	1.183	*a*
Log-likelihood	-5044.515	-4583.119		
χ^2-test	$\chi^2_{0.01} \approx 41.638$ Twice difference of log-likelihood is 922.792			
Number of obs.	3586			
a – normalized to equal one *b* – p-values in paranthesis				

[3] Represents observations where the type of ownership was not identified, which corresponds to 254 observations or about 7 percent of our sample

The LR test allows one to decisively reject the single-equation specification in favor of the switching regression at any conventional significance level.

The returns to education in both segments comply with what one would expect from the dual labor market perspective. Coefficients for all educational levels are positive and statistically significant in the primary sector, while in the secondary sector the coefficient is statistically insignificant for vocational training, negative for general secondary school, and positive but considerably lower for both specialized secondary and university education.

All educational coefficients, except for vocational training, are positive and statistically significant in the switching equation, which suggests that more schooling raises one's chances of belonging to the primary sector.

The returns to working experience is statistically insignificant in the secondary sector, and negative and marginally significant (at the ten-percent significance level) in the primary sector. Although these results are not what the traditional dual labor market theory would predict, they agree with what many researchers find in the transitional countries' context. So, Boeri and Terrell conclude that "in the majority of the transition economies there is strong evidence that the older workers are losing groud to the younger as the experience during the Communist period is not being valued in the labor market". Indeed, many of the skills obtained in the past are obsolete and firm-specific (earlier, we noted that it was a common practice to establish vocational and technical schools supplying specialists for the needs of some large enterprise). Besides, the working discipline and morale in many Soviet-type enterprises were notorious, and long working experience in such a surrounding may be perceived by managers as lowering their ability to affect employee's effort through usual incentives, which, as was explained in the previous section, is critical in the primary sector.

As one would expect, living in Kyiv and being an urban resident raise one's expected wages in both sectors (though the coefficient for Kyiv is insignificant in the secondary sector), and increase the probability of being in the primary sector. Quite unexpectedly, marriage has a negative effect on the probability of primary sector attachment, contrary to what one would expect for the reasons described in on the preceding sections. However, this may be a reflection of the fact that married men are on average both older (42.75 years versus 33.56 years in our sample) and have larger working experience (22.28 years versus 12.87 years) as compared to their unmarried colleagues, which, as we argued above, may have little value in the primary sector.

Once the model is estimated, one may compute the probability that a particular observation is in the primary regime and classify observations to either of the two regimes. We encountered several approaches to this problem in the literature.

Hartley (1978) suggests calculating:

$$\xi_{i3} \equiv E(Y_{i3}^* \mid Y_i) = X_{i3}'\beta_3 - w_1(Y_i)\frac{f_3(0)}{\theta_i} + w_2(Y_i)\frac{f_3(0)}{1-\theta_i} \qquad (13)$$

(where the notation is the same as in equations (4)-(11)), and to assign Y_i to regime 1 if $\xi_{i3} \leq 0$, and to regime 2 if $\xi_{i3} > 0$.

Maddala and Nelson (1974) suggest estimating Θ_i as in equation (10) above. However, Kiefer (1980) argues that this approach does not use all the available sample information, in particular the data on Y_i, and suggests calculating $Pr(Y_i = Y_{i1} \mid Y_i)$, which, applying the Bayes theorem, can be shown (see Maddala, 1983) to be equal to:

$$\Pr(Y_i = Y_{i1} \mid Y_i) = \frac{\Pr(Y_i \mid Y_i = Y_{i1}) * \Pr(Y_i = Y_{i1})}{\Pr(Y_i)} \tag{14}$$

This approach was followed by Dickens and Lang (1985), who calculated the probability for each observation to belong to the primary segment as:

$$\Pr(Y_i = Y_{i1}) = \frac{\Pr(u_{i3} \geq -Z_i\gamma \mid Z_i, X_i, u_{i1}) f(u_{i1})}{\Pr(u_{i3} \geq -Z_i\gamma \mid Z_i, X_i, u_{i1}) f(u_{i1}) + \Pr(u_{i3} < -Z_i\gamma \mid Z_i, X_i, u_{i2}) f(u_{i2})} \tag{15}$$

We follow the approach of Dickens and Lang, and, as a result, the next figure visualizes the distribution of the estimated exp-post probabilities of being in the primary sector.

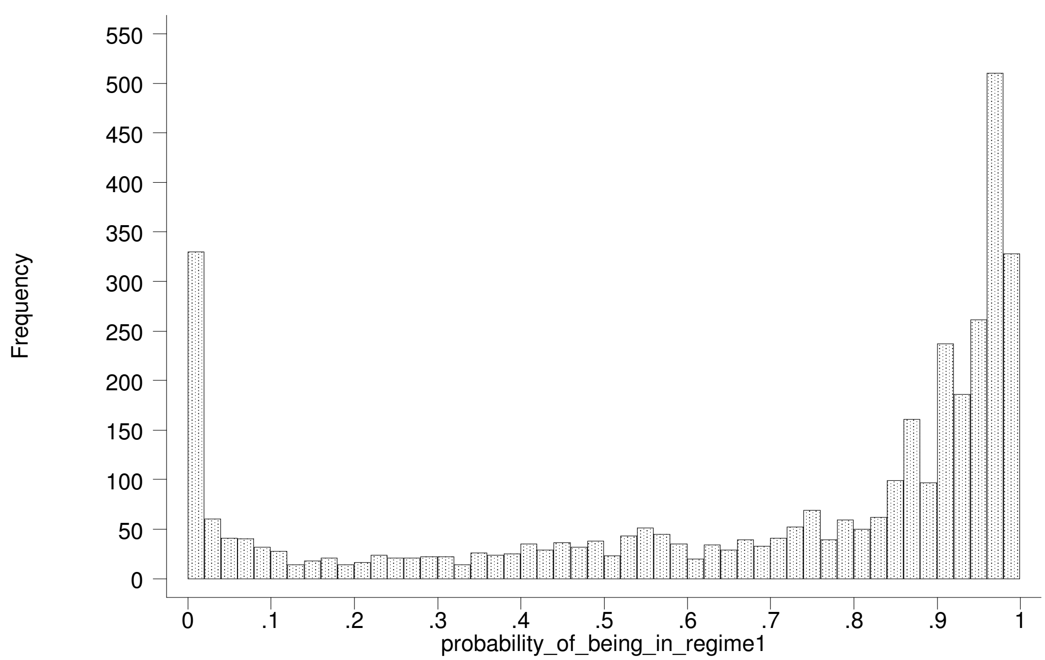

Figure 3. Distribution of Predicted Probabilities of Primary Sector Attachment, Ukrainian Sample

As one may note, the resulting probability distribution is clearly bimodal, with the modes at 0-0.1 and 0.9-1 probability levels, as one could expect from the dual labor market theory perspective. It shows that our model sharply distinguish between the primary and secondary sector workers, identifying a large group of individuals with high probability of secondary-sector attachment.

If one assigned all the observations with predicted primary sector attachment probability of more than 0.5 as belonging to the primary sector, and all the other observations as belonging to the secondary sector, one would get 72.59 percent of the sample (2603 observations) in the primary sector, and 27.41 percent (983 observations) in the secondary sector. At the same time, using the procedure proposed by Hartley would result in 2572 observations (71.72 percent of the sample) being classified into the primary sector, and the remaining 1014 observations (28.28 percent) into the secondary sector.

However, Dickens and Lang (1992) note that the estimated ex post probabilities are the measure of our ignorance, and show how certain we are that a given worker belongs to a certain labor market sector. One can be more certain in classifying an individual observation to one of the sectors if the probability of primary-sector attachment is either close to 1 or 0. The classification of the observations with the estimated probability closer to 0.5 is more problematic. Therefore, Dickens and Lang suggest classifying observations to the primary sector if the estimated probability of being in this sector is larger than 70 percent, and classifying observations to the secondary sector if the estimated probability of belonging to the primary sector is less than 30 percent.

Using the approach of Dickens and Lang, we assigned 2251 observations (62.77 percent of our sample) as belonging to the primary sector, 702 observations (19.58 percent of the sample) as belonging to the secondary sector, with the rest lying in the indeterminate region. Comparing this the results of Dickens and Lang, one may note that the estimated size of the secondary labor market segment is larger in Ukraine than in the United States (about 12 percent, according to the estimations o Dickens and Lang, 1985), which is to be expected, given the volatile nature of the transition process. However, it is smaller than in Chile (where, according to the estimations of Basch and Paredes-Molina, 1995, more than 50 percent of workers are classified to the secondary sector,), or in Estonia (where, according to Lehmann and Luke 2001, the majority of workers find themselves in the secondary segment). The above classification allowed us to calculate some descriptive statistics and composition of the primary segment as compared to that of the whole Ukrainian sample.

Table 2. Descriptive Statistics of the Primary Segment as Compared to the Total Sample, Ukraine

Variable	*Primary Sector**	*Total Sample*
Wages from Primary Job (hrn)	2602.80 (1721.95)**	1940.95 (1834.21)
Age (years)	41.44 (10.70)	41.43 (10.58)
Working Experience (years)	20.98 (11.23)	20.92 (11.07)
Years of Schooling	12.42 (2.74)	11.86 (2.73)

* - assigned to primary sector if the estimated probability of being in the primary sector ≥ 70 percent

** - standard deviation in parenthesis

Table 3. Composition of the Primary Segment as Compared to the Total Sample, Ukraine

Variable	Primary Sector*		Total Sample
	Percent of Primary Sector Workers in Category	Percent of Workers in Each Category in the Primary Sector	
Educational Level:			
Complete Higher Education	33.85	86.89	24.46
Specialized Secondary	22.43	64.17	21.95
Vocational Training	18.92	50.96	23.31
General Secondary	21.06	56.23	23.51
Basic Secondary	3.20	32.88	6.11
Age Profile:			
<25	5.42	65.24	5.21
25-29	10.48	64.13	10.26

30-39	27.45	61.49	28.03
40-49	32.65	62.98	32.54
50-59	18.35	61.37	18.77
60-65	5.64	68.28	5.19
Type of Settlement:			
Urban	93.20	85.22	68.66
Rural	6.80	13.61	31.34
Region:			
Living in Kyiv	7.55	97.70	4.85
Eastern Region	41.00	75.53	34.08
Central Region	19.15	52.75	22.78
Southern Region	12.13	59.35	12.83
Western Region	19.32	48.82	24.85
Married	85.78	62.88	85.64
Type of Ownership:			
State Owned	47.40	70.06	42.47
Foreign Owned	0.93	70	0.84
Wage Arrears:			
Experienced Wage Arrears	19.77	39.84	31.15
Wage Arrears >2000	2.93	54.55	3.37
Wage Arrears 2000-1000	4.18	43.32	6.05
Wage Arrears 1000-500	4.98	38.75	8.06
Wage Arrears 500-300	3.33	39.27	5.32
Wage Arrears <300	4.35	32.78	8.34

* - assigned to the primary sector, if probability of being in the primary sector ≥ 70 percent

As one can note, the estimated mean wages in the primary sector are notably higher than the average in the sample. At the same time, the average age, years of schooling and working experience are quite similar in both the primary sector and the total sample.

One may also note that there are some important differences in the composition of the primary sector as compared to that of the total sample. The primary sector has more than proportional share of people with university education and those who live in cities (the share of rural dwellers in the primary sector is only about 7 percent). Kyiv residents and people who live in a more industrially developed Eastern part of the country are also more than proportionally represented in the primary sector. At the same time, the share of those who live in a more agrarian West is slightly larger in the total sample, as compared to the primary segment.

As is argued in Lehmann and Luke (2001), it is possible that what one would claim to be two labor market segments simply represents different age-earnings profiles at different stages of individuals' working life – with secondary sector consisting of disproportionately high share of young and elderly workers. The estimated composition of the primary segment shows that the age profile in this segment is very similar to that of the whole sample, suggesting that our results are more than just a reflection of two different age-earnings profiles.

There exist some evidence in the literature (for instance, Lehmann et al., 1998) that one of the dominant forms of the labor market adjustment in the transitional labor markets are wage arrears, which are concentrated on a subset of the working population. Our calculations show that workers in the primary sector indeed seem to be less affected by the incidence of wage arrears than those in the whole sample. It lends some support to the view that wage arrears are used by employers to further differentiate the actual wages paid to their employees.

Results for Russian Sample

The major difference between the Russian and Ukrainian data is that reported earnings are annual in the Ukrainian sample, and monthly in the Russian sample.

Russian data contained information on individual's tenure at the current workplace. However, when included in the regression analysis, it turned out to be statistically insignificant in both the OLS regression, and in the two wage equations in the switching regression model. For this reason, and also to allow a more direct comparison of the results for Ukraine and Russia, we omitted it from our regression analysis. The estimated results for the Russian sample are presented below.

Table 4. Switching Regression Model, Russian Sample
Dependent Variable: Log of Wages

Variable	***OLS***	***Primary***	***Second***	***Switching Reg***
high	0.460 (0.000)	0.816 (0.000)	0.408 (0.000)	0.616 (0.000)
ssec	0.289 (0.001)	0.449 (0.005)	0.376 (0.000)	0.642 (0.000)
voc	0.186 (0.020)	0.394 (0.009)	0.220 (0.000)	0.573 (0.000)
csec	0.202 (0.016)	0.501 (0.001)	0.218 (0.000)	0.997 (0.000)
exp	0.019 (0.003)	0.026 (0.024)	0.014 (0.000)	
exp_sec	-0.0004 (0.001)	-0.001 (0.014)	-0.0003 (0.000)	
state	-0.250 (0.000)	-0.070 (0.377)	-0.375 (0.000)	
foreign	0.308 (0.001)	0.273 (0.102)	0.327 (0.000)	
moscow_pet	0.330 (0.000)	-0.247 (0.102)	0.301 (0.000)	-1.406 (0.000)
urban	0.609 (0.000)	0.710 (0.000)	0.390 (0.000)	-0.453 (0.000)
mar	0.155 (0.002)	0.245 (0.006)	0.112 (0.000)	0.047 (0.007)
const	6.930 (0.000)	6.282 (0.000)	7.329 (0.000)	-0.392 (0.000)
St Error	0.851	1.104	0.577	*a*
Log-likelihood	-2089.204	-2029.830		
χ^2-test	$\chi^2_{0.01} \approx 40.289$ Twice difference of log-likelihood is 118.748			
Number of obs.	1661			

a – normalized to equal one
b – p-values in paranthesis

As in the Ukrainian sample, the LR-test rejects the single-equation specification, suggesting that switching regression model fits the data much better than the single equation.

However, in this case the results do not fully comply with the predictions of the dual labor market theory. The returns to all levels of education are positive and statistically significant in both segments, though they are much higher in the primary segment. The returns to general working experience are also positive and statistically significant in both wage regimes. Hence, it is not clear whether the obtained results truly reflect the dual nature of the Russian labor market, or are capturing some non-linearity in the data.

The estimated distribution of probabilities of being in the primary labor market segment are visualized in the following graph:

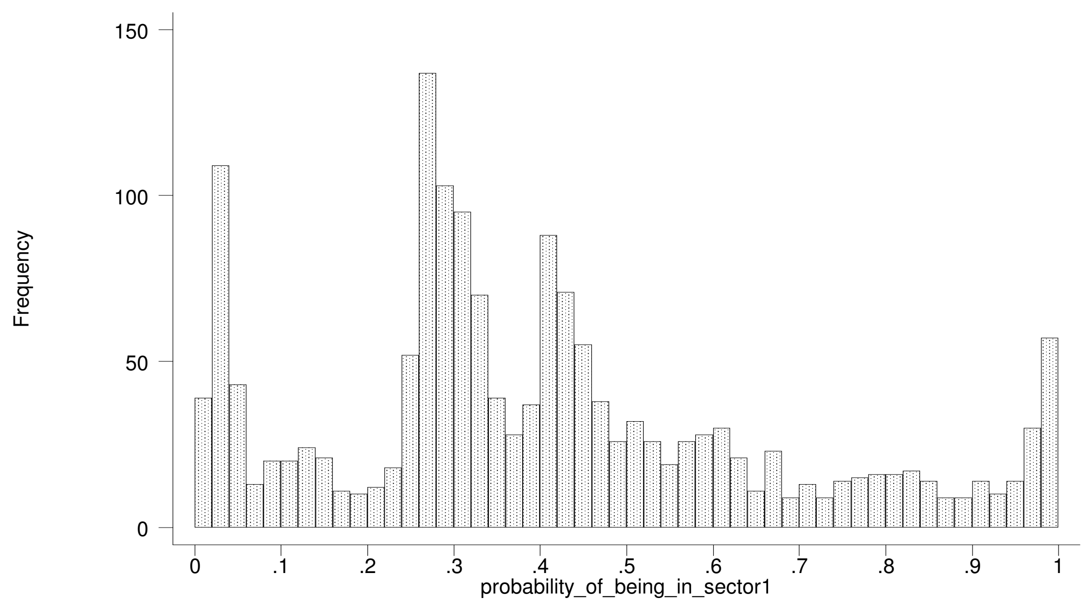

Figure 4. Distribution of Predicted Probabilities of Primary Labor Market Sector Attachment, Russian Sample

Contrary to the Ukrainian case, here the probability distribution does not exhibit a bimodal pattern. It is also clear that most of the workers would be assigned to the secondary segment. Indeed, applying the classification scheme discussed above, we assigned 282 observations (16.98 percent of the sample) to the primary segment, and 632 observations (38.05 percent of the sample) to the secondary segment, with all the rest falling in the indeterminate region. Given that such a large portion of the sample is classified as belonging to the secondary sector, it is doubtful that they all are employed at the manual jobs not requiring either much education or experience. This may partially explain why estimated returns to education are positive in both labor market segments.

Below are given some descriptive statistics and composition of the primary segment as compared to the whole sample.

Table 5. Descriptive Statistics of the Primary Segment as Compared to the Total Sample, Russia.

Variable	*Primary Sector**	*Total Sample*
Wages from Primary Job (rub)	5211.94 (8673.94)**	3795.38 (4369.86)
Age (years)	37.88 (10.82)	38.55 (11.49)
Working Experience (years)	18.21 (11.38)	18.70 (11.82)
Years of Schooling	12.01 (2.60)	12.45 (2.88)

* - assigned to primary sector if the estimated probability of being in the primary sector ≥ 70 percent
** - standard deviation in parenthesis

Table 6. Composition of the Primary Segment as Compared to the Total Sample, Russia

Variable	Primary Sector*		Total Sample
	Percent of Primary Sector Workers in Category	Percent of Workers in Each Category in the Primary Sector	
Educational Level:			

Higher Education	17.02	12.40	22.95
Specialized Secondary	17.73	16.29	18.21
Vocational Training	26.24	14.77	29.72
General Secondary	32.98	28.18	19.57
Basic Secondary	5.67	10.26	9.25
Age Profile:			
<25	13.83	20.21	11.45
25-29	14.18	14.18	16.73
30-39	26.24	16.52	26.57
40-49	31.91	20.55	25.98
50-59	10.28	12.66	13.58
60-65	3.55	10.42	5.69
Type of Settlement:			
Urban	64.54	13.40	80.55
Rural	35.46	30.49	19.45
Region:			
Moscow, St. Petersburg	2.84	3.29	14.41
Northern and North Western	11.70	26.4	7.41
Central and Central Black-Earth	14.18	12.38	19.16
Volga-Vaytski and Volga Basin	16.67	18.08	15.42
North Caucasian	13.83	21.67	10.68
Ural	13.83	15.35	15.07
Western Siberian	14.54	33.33	7.30
Eastern Siberian and Far Eastern	12.41	19.66	10.56
Married	72.70	16.84	72.18
Type of Ownership:			
State Owned	55.32	16	57.83
Foreign Owned	4.61	13.68	5.63
Experienced Wage Arrears	22.34	22.11	16.90
Was Sent on Unpaid Leave During Last Year	2.13	15.38	2.31

* - assigned to the primary sector, if probability of being in the primary sector ≥ 70 percent

In the Russian sample, the primary sector has a lesser share of individuals with university education, but a larger share of those with the general secondary education as compared to the total sample. At the same time, contrary to the Ukrainian case, primary segment in Russia has a lower share of urban residents compared to the total sample.

Koumakhov and Najman (2000) note that sending workers temporarily on unpaid leaves, or using short-time work is an important mechanism of labor adjustment and firms' internal flexibility, and that "firm's behavior in this domain is linked to the labor segmentation" – namely that "administrative-leave-policies reflect firms' efforts to keep employees with specific skills… [and] short-time work is related to continuous, though not always regular demand for elementary professions". Thus, it is possible that widespread forced unpaid leaves, together with wage arrears, are peculiar characteristics of the secondary sector employment in transitional economies. However, our estimated results do not show that primary sector workers are less affected by either wage arrears or forced unpaid leaves. In fact, the incidence of wage arrears is higher among the primary sector workers as compared to the total sample.

Since Russian sample provides information on the employer size, we extend our analysis to test the hypothesis that employer size carries a larger premium in the primary sector by including four dummy variables for different employer size categories – for enterprises with the number of employees between 25 and 99 employees (*size25_99)*, between 100 and 499 employees (*size100_499*), between 500 and 999 employees (*size500_999*), and more than 1000 employees (*size_big*), with small enterprises having less than 25 employees as a base category. Since the data on employer size was lacking for 495 observations (29.80 percent of our sample), we included a dummy for this category as well (*size_un*). The estimation results are presented in Appendix B, Table 9. They show that the employer size premium is indeed larger in the primary sector. The most pronounced difference is observed for the largest employer size category (more than 1000 employees). This is interesting, given that large enterprises in both Ukraine and Russia are predominantly "industrial giants" inherited from the old economic system and are arguably least adapted to operating in the new conditions. Overall, the results from this specification agree with those obtained from the simpler specification (which did not control for the employer size).

Goodness of Fit Test

In one of their subsequent paper Dickens and Lang (1987) answer their critics who claimed that the results from the switching regression analysis might be simply a reflection of the distributional assumptions and may be caused by the complex heteroscedastic nature of the error term, rather than by the genuine duality of the labor market. We follow their approach and compare the results from our switching regression analysis with those obtained from the single labor market specification which explicitly models the heteroscedastic structure of the error term through the two-step FGLS method. Namely, we use the Chernoff-Lehmann goodness of fit test and check how good the two models describe the actual wage distribution[4].

The test is based on splitting the sample into k cells, and comparing the actual number of observations falling into each cell with that predicted by the estimated model, using the following formula:

$$\hat{R} = \sum_{i=1}^{k} (m_i - n\hat{p}_i)^2 / n\hat{p}_i^{\,2}$$

where m_i is the number of observations falling into the ith of the k cells in the data, and $\hat{p}$ is the estimate of the probability of falling into this cell, obtained from

[4] The author is indebted to professors Kevin Lang at Boston University and Peter Kennedy at Simon Fraser University for their invaluable comments on this topic

the model. To calculate $\hat{p}$ from the switching regression model, one may proceed as follows:

let $Y_{i1}=X_{i1}\beta+u_{i1}$ be the wage equation for the primary sector
and let $Y_{i3} = Z_{i1}\gamma+ u_{i3}$ the switching equation, with an observation belonging to the primary sector if $Y_{i3} \geq 0$, and belonging to the secondary sector otherwise.

Then the probability that an individual is in the primary sector and receives a wage in the interval between c_1 and c_2 that corresponds to the *i*th of the *k* cells is the joint probability that $Z_{i1}\gamma+ u_{i3} \geq 0$ and that $c_1< X_{i1}\beta+u_{i1}< c_2$. It is estimated as a double integral of a bivariate normal distribution of u_{i3} and u_{i1}. One may further note that, since we imposed the condition of exogeneity of the switching equation ($\sigma_{13}= \sigma_{23}=0$), it simplifies to the product of two normal cumulative distributions, with the parameters obtained from our estimated model. The probability that an individual is in the secondary sector and his wage falling in this same interval is found similarly. The probability of having a wage in the interval of the *i*th cell is the sum of these two probabilities. Finally, to find the predicted number of individuals in the sample with wages in this interval, one has to sum the estimated probabilities over all individual observations in the sample.

Chernoff and Lehmann (1954) find that the above-mentioned test statistic does not have a limiting χ^2 distribution, if $\hat{p}$-s are the MLE estimates of the true *p-s*, but that its critical values fall between those of the χ^2(k-s-1) and χ^2(k-1) distributions, where *s* is the number of independent parameters being estimated.

To conduct the test, we split our Ukrainian sample into 40 cells, with the lower (200 hryvnias) and upper (11600 hryvnias) bounds chosen so to keep the predicted probabilities from falling well below one. The cell intervals are less than

200 hryvnias, from 200 to 500 hryvnias, 500 to 800, …, 11300 to 11600, and more than 11600 hryvnias. For the interval ranges of both 200 and 250 hryvnias the test-statistic showed that model failed to predict the true wage distribution, which, as is argued by Dickens and Lang, reflects the fact that "all models are wrong".

As a result, the obtained test-statistic is equal to 54.04, which lies in the indeterminate region of the Chernoff-Lehmann test statistic (its upper bound, χ^2(k-1)= χ^2(40-1) with 0.01 significance level is 62.43, with 0.05 significance level - 54.57; and its lower bound, χ^2(k-s-1)= χ^2(40-34-1) with 0.01 significance level is 23.21). Hence, we fail to reject the hypothesis that the switching regression model adequately describes the actual distribution of wages).

To compare the results of our model to those of the single labor market model which allows for complex heteroscedastisity structure, we estimate a two-step FGLS specification. Since our model used 37 parameters, to render a fair comparison, we allowed the alternative model to include 38 parameters – 19 to describe the regression line, and the same 19 to describe the heteroscedastic structure of the disturbance term. To the variables included in the wage equations of the switching regression model, we added interaction terms for each level of education with being and urban resident, and interaction terms for being married and experience, and being an urban resident with experience (several alternative specifications were tried, and this one produced the best fit (minimal Chernoff-Lehmann test statistic). Estimated results obtained from the FGLS specification are given in Appendix B, Table 10. The resulting test-statistic for the FGLS model is 283.94, which is well above the critical values. Thus, the FGLS model can be easily rejected (for comparison, a test statistic for simple single-equation OLS specification is 540.82).

It is possible to visually compare how good the two alternative models predict the actual wage distribution, using the following graph.

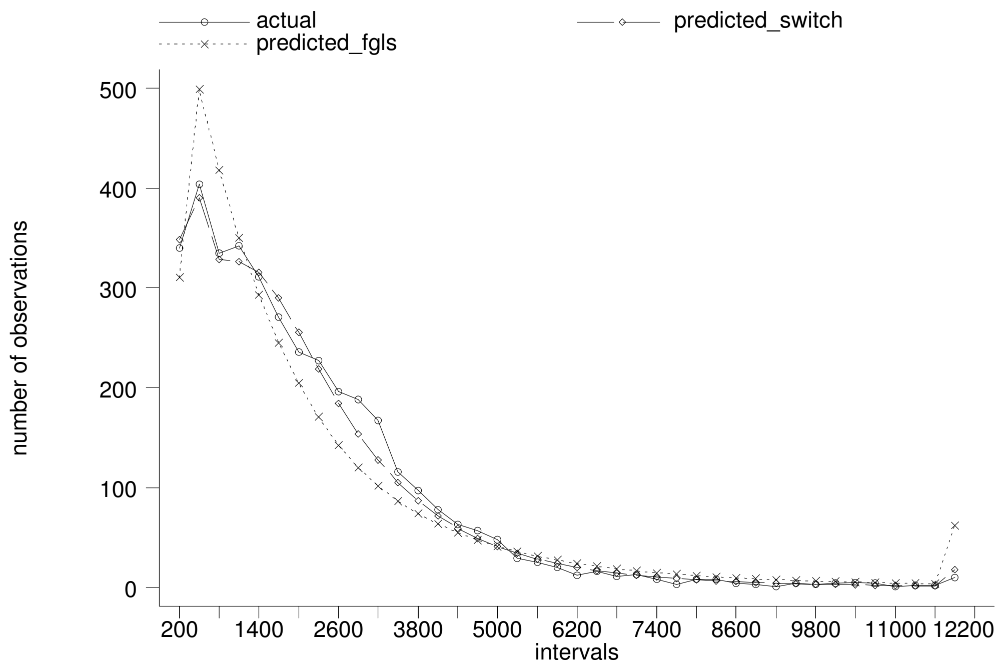

Figure 5. Actual and Predicted Wage Distribution, Ukrainian Sample

It is apparent that switching regression model does a better job in predicting the actual wage distribution, as compared to the FGSL model.

A similar procedure was repeated for the Russian data. Again, we used 40 cells, with the lower bound set at 100 rubles per month, and the upper bound – 19100. The cell intervals ranged from less than 100 rubles, from 100 to 600, 600 to 1100 , … , from 18600 to 19100, and more than 19100 rubles. The obtained Chernoff-Lehmann test statistic for the switching regression model is 271.903, allowing one to easily reject the adequacy of the model. The corresponding test statistic from the FGLS model is 278.89, which is very close to the one for the switching regression (for comparison, the test statistic from the OLS specification was 833.527). The estimated results from fitting the two-step FGLS model to the Russian sample are given in Appendix B, Table 11.

One may also visually compare the predictions obtained from these two models:

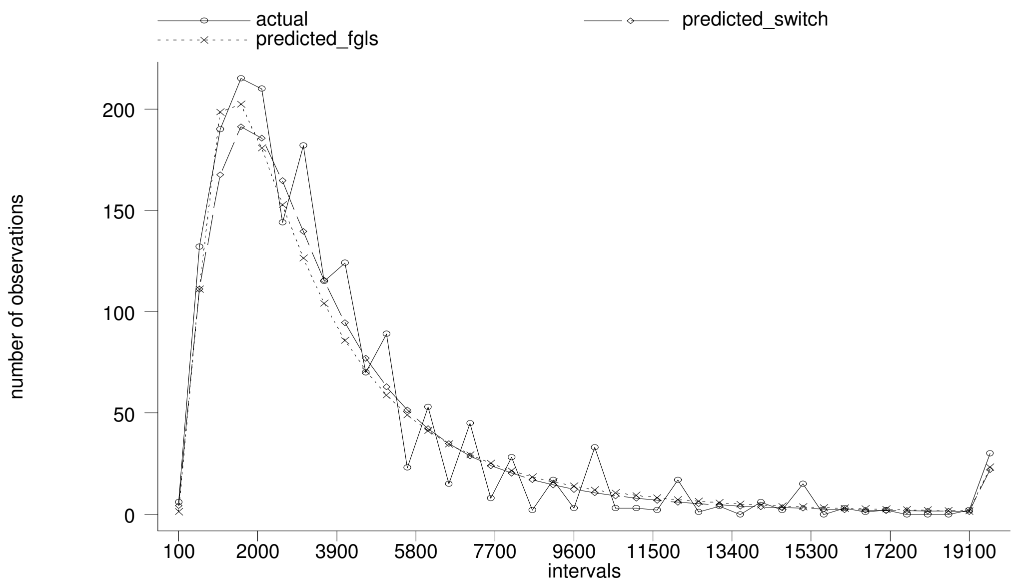

Figure 6. Actual and Predicted Wage Distribution, Russian Sample

Both the goodness of fit test and the visual inspection of the actual and predicted wage distributions show that switching regression model provides little, if any, advantage over the single labor market model with complex heteroscedastic error term in predicting the wage distribution in the Russian case.

Sensitivity Analysis

Lehmann and Luke (2001) note that their results appeared to be sensitive to the specification of the wage and switching equations. This prompted us to check how robust our results are to variations in our model specification.

There is no unanimous agreement whether experience term should be included among the regressors only in wage equations, or both in wage and switching equations of the switching regression model. Dickens and Lang (1985) and Lehmann and Luke (2001) limit experience to their wage equations, while Rebitzer and Robinson (1991) include it (with its square) in the switching equation as well. As was explained earlier, the main criterion which allows one to select regressors for the switching equation is whether they are specific to the individual only, and are not the characteristics of the current workplace. On these grounds, one may conclude that experience is a valid candidate to be included in the switching equation.

The regression results for this extended model specification for the Ukrainian and Russian samples are given in Appendix B (Tables 12 and 13). One may note that they are very similar to those obtained earlier – for the Ukrainian sample, all the educational dummies are statistically significant in the primary segment, and either statistically insignificant, negative or substantially lower in the secondary segment. One may note that the experience term is negative in the switching equation, suggesting that longer experience (most of which was obtained in the old economic system) lowers one's chances to be in the primary segment, supporting our earlier conjecture that this experience is poorly priced by the market. The following graph suggests that our model sharply distinguish between the primary and secondary sectors, as the distribution of predicted probabilities of primary sector attachment is distinctly bimodal, with the modes of 0-0.1 and 0.9-1 probabilities.

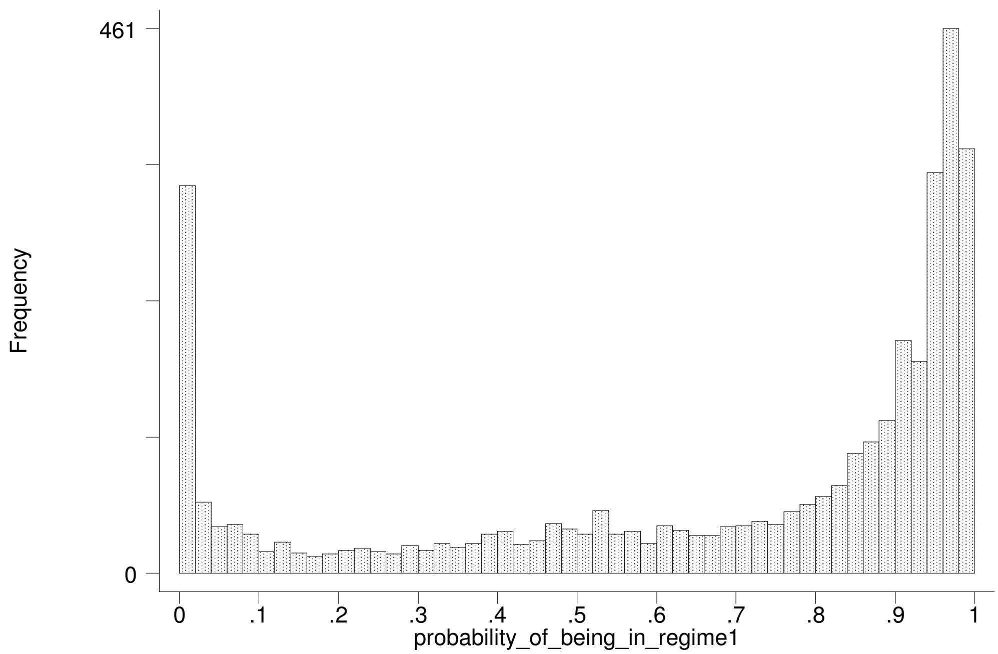

Figure 7. Distribution of Predicted Probabilities of Primary Sector Attachment, Ukrainian Sample (with Experience term included in the switching regression).

The results for the Russian sample are also very close to those obtained earlier. Contrary to the Ukrainian sample, in the Russian case the experience term in positive in the switching regression. The following graph shows the distribution of predicted probabilities of primary sector attachment in the Russian sample. One may note that the extended model, as well as the simpler one, does not provide a sharp distinction between the two sectors.

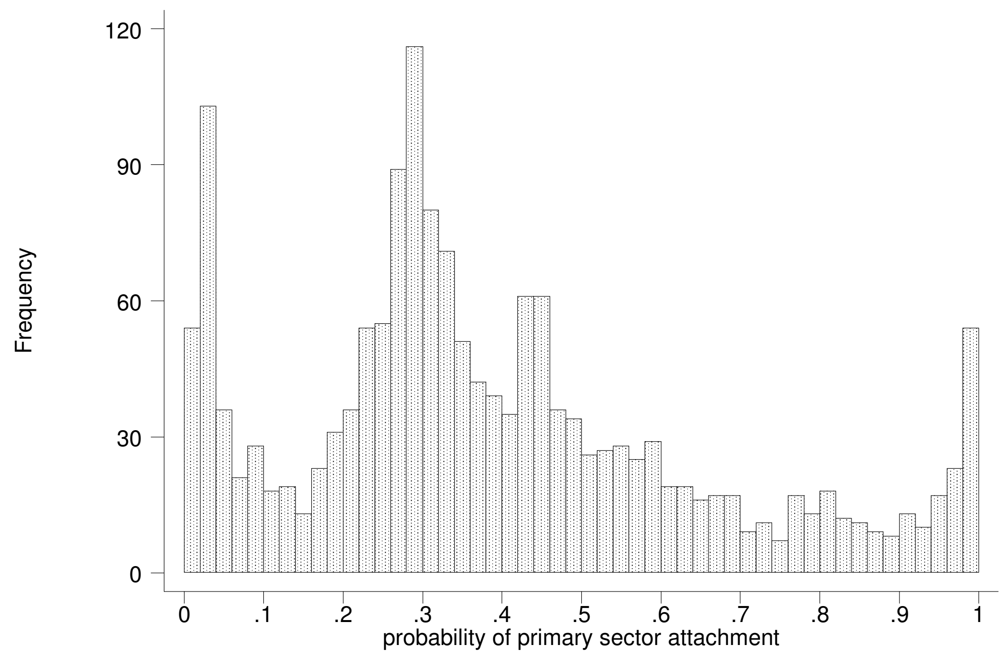

Figure 8. Distribution of Predicted Probabilities of Primary Sector Attachment, Russian Sample (with Experience term included in the switching regression)

One could note from our previous analysis that there were some notable differences in the geographical composition of the two sectors in both countries (see Tables 3 and 6). To account for the possibility of geographical segmentation of the two countries' labor markets, we further extended our model by including regional dummies into both wage and switching equations. The results are presented in Appendix B, Tables 14 and 15. As one may note, they are very similar to those obtained earlier. In the Ukrainian case, all the regional dummies are negative and statistically significant in the switching regression, suggesting that individuals living in the Eastern region (base category) have higher chances of obtaining primary-sector jobs as compared to other workers.

In the Russian sample, living in the Northern or Western Siberian regions raises one's chances of primary sector attachment compared to those who live in Eastern Siberia and Far East (base category), while living in all other regions (including the metropolitan areas of Moscow and St. Petersburg) lowers them.

Our sensitivity analysis suggests that our results are quite robust to the model specification variations.

Chapter 5

SUMMARY AND CONCLUSIONS

This study has been devoted to testing the labor market segmentation theory in the context of transitional economies of Ukraine and Russia. Most of the existing empirical research of the earnings structure in transitional economies concentrate on predictions of the standard human capital theory, implying that the miserable fate of the rapidly increasing class of low-earners in these countries is the consequence of the lack of appropriate skills and knowledge necessary to obtain a desirable job. Contrary to this view, dual labor market theory argues that the wage structure of low-earners would be different from that of high-wage workers, and that the equilibrium in the labor market may be characterized by rationing of high-wage desirable jobs, with "good" workers stuck in "bad" jobs.

Our switching regression analysis showed that there indeed appear to be two distinct wage-setting mechanisms for the sub-groups of low-wage and high-wage workers in the Ukrainian labor market, with increasing returns to education in the primary labor market segment, and much smaller (for some educational categories – zero or negative) returns in the secondary sector. At the same time, our analysis suggests that general working experience is not a valuable asset in either of the labor market segments in Ukraine. Our estimated model allows one to sharply distinguish between the two groups of workers – those who are clearly identifiable as primary-sector workers, and a substantial group of those who have high probability of secondary-sector attachment.

Similar analysis conducted for Russia produced ambiguous results. Although formal test corroborates the hypothesis that switching regression model fits the data significantly better than the single-equation specification, the distinction in the wage-setting mechanisms in the two sectors is rather blurred, with non-negligible positive returns to education and experience in both sectors. There may be several potential explanations for this finding. One is that Russian labor market is indeed rather homogeneous, and that our results are only capturing some non-linearities in the wage-setting mechanism. However, noting that the estimated size of the secondary labor market segment in Russia is rather large (covering almost 40 percent of our sample), it is dubious that jobs in this sectors are mainly temporary and manual, as is usually held by dual labor market theory. Hence, one could hardly expect flat education-earnings profile for such a substantial part of the labor market.

Recognizing that our results is equivalent to assuming a particular (heteroscedastic) distribution of the error term, we subjected our model to a goodness of fit test, comparing it to a single-equation specification which assumes a quite complex heteroscedastic nature of the errors. The results show that in the Ukrainian sample, switching regression outperforms the single-equation specification by a large margin, while in the Russian case, the switching regression model offers little advantage in predicting the true wage distribution.

Furthermore, we undertook some sensitivity analysis, which showed that our results for both Ukraine and Russia are robust to variations in the model specification.

Hence, our results show that Ukrainian labor market is better explained in terms of the dual labor market model. At the same time, we did not find conclusive support to the dual labor market hypothesis in the Russian case. This may be due to the fact, that the model needs some modification for the transitional context, which requires further theoretical and empirical research into the realm of labor market segmentation in the countries of transition.

A promising direction of further research would be relaxing the assumption of exogeneous switching, imposed in our model. Besides, it would be interesting to investigate how the labor markets in both countries develop over time, once the data covering a longer time span will be available.

BIBLIOGRAPHY

Akerlof, G. 1982. "Labor Contracts as Partial Gift Exchange", *The Quarterly Journal of Economics*, Vol.97, Issue4, pp. 543-569.

Boeri, Tito and Christopher J. Flinn. 1997. "Returns to Mobility in the Transition to a Market Economy", New York, C.V. Starr Center – Working Paper # 9741.

Boeri, Tito and Katherina Terrell. 2001. "Institutional Determinants of Labor Reallocation in Transition", *William Davidson Working Paper #384*

Bosanquet, N. and P. Doeringer. 1973. "Is There a Dual Labour Market in Great Britain?", *The Economic Journal*, Vol. 83, Issue 330, pp. 421-435.

Bowles, S. and H. Gintis. 1975. "The Problem with Human Capital Theory – A Marxian Critique", *The American Economic Review*, Vol, 65, Issue 2, pp. 74-82.

Bowles, S. 1985. "The Production Process in a Competitive Economy: Walrasian, Neo-Hobbesian, and Marxian Models", *American Economic Review,* Vol.75., Issue 1, pp.16-36.

Brainerd, E. 1998. "Winners and Losers in Russia's Economic Transition", *The American Economic Review*, Vol. 88, Issue 5, pp. 1094-1116.

Bulow, J. and L. Summers. 1986. "A Theory of Dual Labor Markets with Application to Industrial Policy, Discrimination, and Keynesian Unemployment", *Journal of Labor Economics*, Vol. 4, Issue 3, Part 1, pp. 376-414.

Cain, G. 1976. "The Challenge of Segmented Labor Market Theories to Orthodox Theory: A Survey", *Journal of Economic Literature*, Vol. 14, Issue 4, pp. 1215-1257.

Chernoff H. and E.L. Lehmann. 1954. "The Use of Maximum Likelihood Estimates in Chi-Squared Tests for Goodness of Fit", *Annals of Mathematical Statistics,* Vol.25, Issue 3, pp. 579-586.

Commander, S. et al. 1999. "Channels of Redistribution: Inequality and Poverty in the Russian Transition", *The Economics of Transition,* 7, pp. 411-447,

Dickens, W. and K. Lang. 1985. "A Test of Dual Labor Market Theory", *The American Economic Review*, Vol. 75, Issue 4, pp. 792-805.

Dickens, W. and K. Lang. 1987. "A Goodness of Fit Test of Dual Labor Market Theory", *NBER Working Paper # 2350*.

Dickens, W. and K. Lang. 1987. "Neoclassical and Sociological Perspectives on Segmented Labor Markets", *NBER Working Paper #2127*

Dickens, W. and K. Lang. 1988. "The Reemergence of Segmented Labor Market Theory", *The American Economic Review*, Vol. 78, Issue 2, pp. 129-134.

Dickens, W. and K. Lang. 1992. "Labor Market Segmentation Theory: Reconsidering the Evidence", *NBER Working Paper #4087*.

Elbaum, B. 1983. "The Internalization of Labor Markets: Causes and Consequences", *The American Economic Review*, Vol. 73, Issue 2, pp. 260-265.

Garner, Thesia and Katherine Terrell. 1998. "A Gini Decomposition Analysis of Inequality in the Czech and Slovak Republics During the Transition", *The Economics of Transition,* 6, pp. 23-46.

Goldfeld, Steven M. and Richard E. Quandt. 1976. "Techniques for Estimating Switching Regressions" in their *Studies in Non-Linear Estimation.*

Grosfeld, Irena et al. 1999. "Dynamism and Inertia on the Russian Labor Market: A Model of Segmentation". *William Davidson Institute Working Paper # 246*.

Hartley, Michael J. 1978. "Estimating Mixtures of Normal Distributions and Switching Regressions: Comment", *Journal of the American Statistical Association,* Vol.73, Issue 364, pp.738-741.

Heckman, J. and J. Hotz. 1986. "An Investigation of the Labor Market Earnings of Panamian Males: Evaluating the Sources of Inequality", *The Journal of Human Resources*, Vol. 21, Issue 4, pp. 507-542.

Kiefer, Nicholas M. 1980. "A Note on Switching Regressions and Logistic Discrimination", *Econometrica,* Vol. 48, Issue 4, pp.1065-1069.

Koumakhov, R and B. Najman. 2001. "Labor Hoarding in Russia: Where Does it Come From?", *William Davidson Institute Working Paper #394*.

Lee, Lung-Fei and Robert H. Porter. 1984. "Switching Regression Models with Imperfect Sample Separation Information – With an Application on Cartel Stability", *Econometrica,* Vol. 52, Issue 2, pp.391-418.

Lehmann et al. 1998. "Grime and Punishment: Job Insecurity and Wage Arrears in the Russian Federation", *CEP Discussion Papers,* available at http://netec.mcc.ac.uk

Lehmann, H. and P. Luke. 2001. "Labour Market Sementation in Estonia During the First Decade of Transition", Heriot-Watt University of Edinburgh, mimeo.

Maddala, G.S. 1983. *Limited Dependent and Qualitative Variables in Econometrics.* New York: Cambridge University Pres.

Maddala, G.S. 1986. "Disequilibrium, Self-Selection, and Switching Models" *in "Handbook of Econometrics",* Vol. III. Elsevier Science Publishers BV, pp.1634-1688.

Magnac, Th. 1991. "Segmented of Competitive Labor Markets?", *Econometrica*, Vol. 59, No. 1. pp. 165-187.

Milanovic, B. 1998 "Income, Inequality and Poverty During the Transition from Planned to Market Economy", *World Bank Regional and Sectoral Studies*.

Moore, David S. 1977. "Generalized Inverses, Wald's Method, and the Construction of Chi-Squared Tests of Fit", *Journal of the American Statistical Association,* Vol.72, Issue 357, pp.131-137.

Osterman, Paul. 1975. "An Empirical Study of Labor Market Segmentation", *Industrial and Labor Relations Reviw,* Vol.28, Issue 4, pp.508-523.

Pinera, S., Selowsky, M. 1978 "The Opportunity Cost of Labor and the Returns to Education under Unemployment and Labor Market Segmentation", *The Quarterly Journal of Economics*, Vol. 92, Issue 3, pp. 469-488.

Piore, M. 1973. "Fragmets of a "Sociological"Theory of Wages", *The American Economic Review*, Volume 63, Issue 2, pp. 377-384.

Piore, M. (1983) "Labor Market Segmentation: To What Paradigm Does it Belong?", *The American Economic Review*, Vol. 73, Issue 2, pp. 249-253.

Quandt, Richard E and James B. Ramsey. 1978. "Estimating Mixtures of Normal Distributions and Switching Regressions" *Journal of the American Statistical Association,* Vol. 73, Issue 364, pp.730-738.

Rebitzer, J. and M. Robinson. 1991. "Employer Size and Dual Labor Markets", *The Review of Economics and Statistics*, Vol. 73, Issue 4, pp. 710-715.

Rebitzer, J. and L. Taylor. 1991. "A Model of Dual Labor Markets When Product Demand is Uncertain", *The Quarterly Journal of Economics*, Vol. 106, Issue 4, pp. 1373-1383.

Reich, M., Gordon, D., Edwards, R. 1973. "A Theory of Labor Market Segmentation", *The American Economic Review*, Vol.63, Issue 2, pp. 359-365.

Roemer, John E. 1979. "Divide and Conquer: Microfoundations of a Marxian Theory of Wage Determination", *Bell Journal of Economics,* 10(2), pp.695-705.

Shapiro, Carl and Joseph E. Stiglitz. "Equilibrium Unemployment as a Worker Disciplining Device", *The American Economic Review,* Vol.74, Issue 3, pp.433-444.

Solow, R. 1979. "Alternative Approaches to Macroeconomic

Theory: A Partial View", *Can.J.Econ.,* Vol.12, pp.339-354.

Solow, R. 1980. "On Theories of Unemployment", *American Economic Review,* Vol.70, Issue 1, pp.1-11.

Spence, M. 1973. "Job Market Signalling", *The Quarterly Journal of Economics*, Vol. 87, Issue 3, pp. 355-374.

Vietorisz, T. and B. Harrison. 1973. "Labor Market Segmentation: Positive Feedback and Divergent Development", *The American Economic Review*, Vol. 63, Issue 2, pp. 366-376.

Weitzman, M. 1989. "A Theory of Wage Dispersion and Job Market Segmentation", *The Quarterly Journal of Economics*, Vol. 104, Issue 1, pp. 121-137.

Yellen, Janet L. 1984. "Efficiency Wage Models of Unemployment", *The American Economic Review,* Vol. 74, Issue 2, pp.200-205.

Appendix A

Table 7. Definition of Variables Used in Regression Analysis (Ukrainian Sample).

Variables	Definition
Educational Categories (basic secondary or lower as a base category)	
csec	Equals 1 if the person completed 10-11 years of general secondary school and received a high school diploma, 0 otherwise
voc	Equals 1 if the person completed a vocational training school, 0 otherwise
ssec	Equals 1 if the person obtained a specialized technical/medical education ("technicum"), 0 otherwise
high	Equals 1 if the person has some university education, 0 otherwise
exp	Number of years of general working experience
exp_sq	Experience squared
Type of Ownership (domestic non-state as a base category)	
state	Equals 1 if the enterprise is state-owned, 0 otherwise
foreign	Equals 1 if the enterprise is either a joint-venture, or owned by foreigners, 0 otherwise
kyiv	Equals 1 if the person lives in the capital city of Kyiv, 0 otherwise
Geographical Regions (living in the Eastern region as a base category)	
west	Equals 1 if the person lives in the Western region of Ukraine, 0 otherwise
center	Equals 1 if the person lives in the Central region of Ukraine, 0 otherwise
south	Equals 1 if the person lives in the Southern region of Ukraine, 0 otherwise
Type of Residential Center (rural residents as a base category)	
urban	Equals 1 if the person lives in a large town, 0 otherwise
married	Equals 1 if the person is married, 0 otherwise

Table 8. Description of Variables Used in Regression Analysis (Russian Sample)

Variables	Definition
Educational Categories (basic secondary or lower as a base category)	
csec	Equals 1 if the person completed 10-11 years of general secondary school and received a high school diploma, 0 otherwise
voc	Equals 1 if the person completed a vocational training school, 0 otherwise
ssec	Equals 1 if the person obtained a specialized technical/medical education ("technicum"), 0 otherwise
high	Equals 1 if the person obtained a university diploma, 0 otherwise
exp	Number of years of general working experience
exp_sq	Experience squared
tenure	Number of month worked at present job
tenure_sq	Tenure squared
Type of Ownership (domestic non-state as a base category)	
state	Equals 1 if the enterprise is state-owned, 0 otherwise
foreign	Equals 1 if the enterprise is either a joint-venture, or owned by foreigners, 0 otherwise
Geographical Regions (living in the Eastern Siberian and Far Eastern region as a base category)	
moscow_pet	Equals 1 if the person lives in metropolitan areas of Moscow and St. Petersburg, 0 otherwise
north	Equals 1 if the person lives in the Northern or North Western region, 0 otherwise
central	Equals 1 if the person lives in the Central and Central Black-Earth resion, 0 othewise
volga	Equals 1 if the person lives in the Volga-Vyatski and Volga Basin region, 0 otherwise
caucus	Equals 1 if the person lives in the North Caucasian region, 0 otherwise
ural	Equals 1 if the person lives in the Ural region, 0 otherwise
west_sib	Equals 1 if the person lives in the Western Siberian region, 0 otherwise
Type of Residential Center (rural residents as a base category)	
large_town	Equals 1 if the person lives in a large town, 0 otherwise
small_town	Equals 1 if the person lives in a small town, 0 otherwise
Size of the Enterprise (less than 25 employees as a base category)	
size100	Equals 1 if enterprise employs 25-100 employees, 0 otherwise
size200	Equals 1 if enterprise employs 101-200 employees, 0 otherwise
size500	Equals 1 if enterprise employs 201-500 employees, 0 otherwise
size1000	Equals 1 if enterprise employs 501-1000 employees, 0 otherwise
sizebig	Equals 1 if enterprise employs more than 1000 employees, 0 otherwise
sizeun	Equals 1 if the number of employees is unknown, 0 otherwise
married	Equals 1 if the person is married, 0 otherwise

Appendix B

Table 9. Switching Regression Model, Controlling for Employer Size. Russian Sample

Dependent Variable: Log of Wages

Variable	***OLS***	***Primary***	***Second***	***Switching Reg***
high	0.467 (0.000)	0.920 (0.000)	0.444 (0.000)	0.685 (0.000)
ssec	0.301 (0.000)	0.593 (0.000)	0.391 (0.000)	0.769 (0.000)
voc	0.184 (0.020)	0.495 (0.001)	0.224 (0.000)	0.680 (0.000)
csec	0.206 (0.013)	0.601 (0.000)	0.228 (0.000)	1.035 (0.000)
exp	0.021 (0.001)	0.028 (0.020)	0.018 (0.000)	
exp_sec	-0.001 (0.000)	-0.001 (0.011)	-0.0004 (0.000)	
size25_99	-0.024 (0.751)	0.161 (0.214)	-0.149 (0.005)	
size100_499	0.117 (0.122)	0.368 (0.005)	-0.003 (0.956)	
size500_999	0.152 (0.148)	0.229 (0.147)	0.117 (0.103)	
size_big	0.374 (0.000)	0.862 (0.000)	0.124 (0.028)	
size_un	0.101 (0.143)	0.360 (0.005)	-0.029 (0.546)	
state	-0.293 (0.000)	-0.082 (0.306)	-0.424 (0.000)	
foreign	0.185 (0.052)	-0.046 (0.782)	0.290 (0.000)	
moscow_pet	0.346 (0.000)	-0.119 (0.421)	0.283 (0.000)	-1.434 (0.000)
urban	0.550 (0.000)	0.596 (0.000)	0.339 (0.000)	-0.508 (0.000)
mar	0.131 (0.008)	0.272 (0.002)	0.068 (0.047)	0.068 (0.000)
const	6.894 (0.000)	5.888 (0.000)	7.408 ()	-0.518 (0.000)
St Error	0.837	1.087	0.585	*a*
Log-likelihood	-2073.681	-2009.945		
χ^2-test	$\chi^2_{0.01} \approx 68.71$ Twice difference of log-likelihood is 127.472			
Number of obs.	1661			
a – normalized to equal one *b* – p-values in paranthesis				

Table 10. Two-Step FGLS model (Ukrainian Sample).

Dependent Variable: Log of Wages in Regression Line Equation, Squared Error Term from OLS Specification in the Error Term Equation

Variable	***Regression Line Equation***	***Error Term Equation***
high	0.728 (0.000)	-0.153 (0.498)
ssec	0.372 (0.004)	0.342 (0.100)
voc	0.178 (0.151)	0.256 (0.202)
csec	-0.079 (0.518)	0.426 (0.028)
exp	-0.079 (0.986)	0.015 (0.149)
exp_sq	-0.079 (0.028)	0.00004 (0.710)
state	0.116 (0.000)	-0.370 (0.000)
foreign	0.711 (0.000)	-0.611 (0.078)
prop_un	-1.100 (0.000)	-0.097 (0.444)
kyiv	0.584 (0.000)	-0.338 (0.023)
urban	0.8586 (0.000)	-0.297 (0.311)
mar	0.283 (0.000)	0.471 (0.002)
urban_high	-0.193 (0.219)	-0.164 (0.581)
urban_ssec	-0.027 (0.868)	-0.571 (0.046)
urban_voc	-0.039 (0.803)	-0.104 (0.713)
urban_sces	-0.039 (0.328)	-0.497 (0.073)
mar_exp	-0.003 (0.451)	-0.018 (0.026)
urban_exp	0.001 (0.738)	0.003 (0.653)
const	6.101 (0.000)	0.943 (0.000)
R-squared	0.9864	0.0516
F-test	13513.14	10.79
Number of obs.	3586	
a – p-values in paranthesis		

Table 11. Two-Step FGLS model (Russian Sample).

Dependent Variable: Log of Wages in Regression Line Equation, Squared Error Term from OLS Specification in the Error Term Equation

Variable	***Regression Line Equation***	***Error Term Equation***
high	0.581 (0.000)	-0.104 (0.695)
ssec	0.259 (0.203)	0.435 (0.094)
voc	0.123 (0.396)	0.250 (0.224)
csec	0.093 (0.580)	0.394 (0.080)
exp	0.025 (0.000)	0.011 (0.349)
exp_sq	-0.0004 (0.000)	-0.0004 (0.095)
state	-0.287 (0.000)	-0.131 (0.036)
foreign	0.311 (0.000)	-0.094 (0.482)
moscow_pet	0.301 (0.000)	-0.327 (0.000)
urban	0.537 (0.001)	-0.216 (0.380)
mar	0.142 (0.054)	-0.030 (0.804)
urban_high	-0.084 (0.646)	0.279 (0.350)
urban_ssec	0.088 (0.687)	-0.327 (0.270)
urban_voc	0.149 (0.360)	-0.141 (0.568)
urban_sces	0.196 (0.300)	-0.099 (0.568)
mar_exp	-0.003 (0.000)	0.002 (0.699)
urban_exp	-0.002 (0.354)	0.007 (0.298)
const	6.931 (0.694)	0.729 (0.001)
R-squared	8598.27	0.0254
F-test	8598.27	2.52
Number of obs.		
a – p-values in paranthesis		

Table 12. Switching Regression Model (with Experience and Experience Squared Included in the Switching Equation), Ukrainian Sample

Dependent Variable: Log of Wages

Variable	***OLS***	***Primary***	***Second***	***Switching Reg***
high	0.607 (0.000)	0.515 (0.000)	0.325 (0.008)	0.670 (0.000)
ssec	0.394 (0.000)	0.369 (0.000)	0.270 (0.018)	0.268 (0.000)
voc	0.178 (0.016)	0.328 (0.000)	0.146 (0.172)	-0.079 (0.013)
csec	0.057 (0.439)	0.157 (0.001)	-0.224 (0.037)	0.185 (0.000)
exp	-0.007 (0.059)	-0.004 (0.176)	0.012 (0.047)	-0.017 (0.000)
exp_sec	-0.0001 (0.278)	-0.0001 (0.160)	-0.0003 (0.000)	0.0001 (0.000)
state	0.241 (0.000)	-0.084 (0.000)	0.985 (0.000)	
foreign	0.744 (0.000)	0.307 (0.001)	1.898 (0.000)	
prop_un	-1.077 (0.000)	-1.183 (0.000)	-0.640 (0.000)	
kyiv	0.588 (0.000)	0.423 (0.000)	0.233 (0.320)	0.943 (0.000)
urban	0.924 (0.000)	0.472 (0.000)	0.168 (0.005)	1.250 (0.000)
mar	0.216 (0.000)	0.298 (0.000)	0.030 (0.734)	-0.028 (0.205)
const	6.074 (0.000)	6.760 (0.000)	5.497(0.000)	-0.295 (0.000)
St Error	0.988	0.583	1.181	*a*
Log-likelihood	-5044.515	-4581.267		
χ^2-test	$\chi^2_{0.01} \approx 44.314$ Twice difference of log-likelihood is 926.497			
Number of obs.	3586			
a – normalized to equal one *b* – p-values in paranthesis				

Table 13. Switching Regression Model (with Experience and Experience Squared Included in the Switching Equation), Russian Sample

Dependent Variable: Log of Wages

Variable	***OLS***	***Primary***	***Second***	***Switching Reg***
high	0.460 (0.000)	0.878 (0.000)	0.393 (0.000)	0.595 (0.000)
ssec	0.289 (0.001)	0.512 (0.002)	0.344 (0.000)	0.600 (0.000)
voc	0.186 (0.020)	0.437 (0.004)	0.209 (0.000)	0.557 (0.000)
csec	0.202 (0.016)	0.547 (0.001)	0.213 (0.000)	0.998 (0.000)
exp	0.019 (0.003)	0.030 (0.016)	0.017 (0.000)	0.033 (0.000)
exp_sec	-0.0004 (0.001)	-0.001 (0.010)	-0.0004 (0.000)	-0.001 (0.000)
state	-0.250 (0.000)	-0.063 (0.439)	-0.370 (0.000)	
foreign	0.308 (0.001)	0.304 (0.079)	0.307 (0.000)	
moscow_pet	0.330 (0.000)	-0.258 (0.086)	0.304 (0.000)	-1.387 (0.000)
urban	0.609 (0.000)	0.702 (0.000)	0.414 (0.000)	-0.439 (0.000)
mar	0.155 (0.002)	0.245 (0.008)	0.113 (0.001)	0.008 (0.651)
const	6.930 (0.000)	6.200 (0.000)	7.287 (0.000)	-0.698 (0.000)
St Error	0.851	1.115	0.585	*a*
Log-likelihood	-2089.204	-2029.114		
χ^2-test	$\chi^2_{0.01} \approx 42.980$ Twice difference of log-likelihood is 120.18			
Number of obs.	1661			
a – normalized to equal one *b* – p-values in paranthesis				

Table 14. Switching Regression Results, Controlling for Geographical Regions, Ukrainian Sample

Dependent Variable: Log of Wages

Variable	***OLS***	***Primary***	***Second***	***Switching Reg***
high	0.599 (0.000)	0.518 (0.000)	0.305 (0.012)	0.690 (0.000)
ssec	0.368 (0.000)	0.351 (0.000)	0.229 (0.047)	0.280 (0.000)
voc	0.152 (0.038)	0.316 (0.000)	0.123 (0.254)	-0.102 (0.001)
csec	0.046 (0.523)	0.163 (0.001)	-0.201 (0.061)	0.144 (0.000)
exp	-0.007 (0.046)	-0.004 (0.171)	0.009 (0.146)	-0.017 (0.000)
exp_sec	-0.0001 (0.266)	-0.0001 (0.153)	-0.0003 (0.000)	0.0002 (0.000)
state	0.249 (0.000)	-0.073 (0.000)	0.979 (0.000)	
foreign	0.798 (0.000)	0.355 (0.000)	1.917 (0.000)	
prop_un	-1.070 (0.000)	-1.162 (0.000)	-0.652 (0.000)	
kyiv	0.429 (0.000)	0.306 (0.000)	0.069 (0.773)	0.848 (0.000)
center	-0.275 (0.000)	-0.151 (0.000)	-0.284 (0.001)	-0.168 (0.000)
south	-0.214 (0.000)	-0.235 (0.000)	-0.076 (0.416)	-0.047 (0.049)
west	-0.330 (0.000)	-0.239 (0.000)	-0.233 (0.004)	-0.283 (0.000)
urban	0.846 (0.000)	0.423 (0.000)	0.134 (0.031)	1.203 (0.000)
mar	0.224 (0.000)	0.311 (0.000)	0.029 (0.739)	-0.035 (0.111)
const	6.319 (0.000)	6.910 (0.000)	5.748 (0.000)	-0.142 (0.000)
St Error	0.959	0.571	1.175	*a*
Log-likelihood	-5011.841	-4536.839		
χ^2-test	$\chi^2_{0.01} \approx 52.191$ Twice difference of log-likelihood is 950.004			
Number of obs.	3586			
a – normalized to equal one *b* – p-values in paranthesis				

Table 15. Switching Regression Model, Controlling for Geographical Regions, Russian Sample

Dependent Variable: Log of Wages

Variable	***OLS***	***Primary***	***Second***	***Switching Reg***
high	0.468 (0.000)	0.823 (0.000)	0.440 (0.000)	0.229 (0.000)
ssec	0.282 (0.001)	0.554 (0.004)	0.299 (0.000)	0.411 (0.000)
voc	0.169 (0.030)	0.426 (0.014)	0.166 (0.004)	0.280 (0.000)
csec	0.202 (0.014)	0.553 (0.002)	0.235 (0.000)	0.704 (0.000)
exp	0.020 (0.002)	0.042 (0.009)	0.024 (0.000)	0.064 (0.000)
exp_sec	-0.001 (0.000)	-0.001 (0.008)	-0.001 (0.000)	-0.001 (0.000)
state	-0.239 (0.000)	-0.009 (0.921)	-0.329 (0.000)	
foreign	0.341 (0.000)	0.602 (0.007)	0.275 (0.000)	
moscow_pet	0.180 (0.035)	-0.409 (0.054)	0.081 (0.174)	-1.403 (0.000)
north	0.334 (0.001)	0.643 (0.000)	0.192 (0.006)	1.049 (0.000)
central	-0.223 (0.005)	-0.836 (0.000)	-0.188 (0.001)	-0.600 (0.000)
volga	-0.438 (0.000)	-0.800 (0.000)	-0.438 (0.000)	-0.470 (0.000)
caucus	-0.207 (0.021)	0.131 (0.465)	-0.389 (0.000)	-0.138 (0.000)
ural	-0.103 (0.218)	-0.438 (0.020)	-0.119 (0.036)	-0.558 (0.000)
west_sib	0.036 (0.717)	0.383 (0.033)	-0.366 (0.000)	1.519 (0.000)
urban	0.638 (0.000)	0.808 (0.000)	0.466 (0.000)	-0.369 (0.000)
mar	0.157 (0.001)	0.307 (0.002)	0.088 (0.019)	-0.056 (0.002)
const	7.035 (0.000)	5.922 (0.000)	7.377 (0.000)	-1.004 (0.000)
St Error	0.688	1.113	0.613	*a*
Log-likelihood	-2046.212	-1954.7051		
χ^2-test	$\chi^2_{0.01}\approx 58.619$ Twice difference of log-likelihood is 183.014			
Number of obs.	1661			

a – normalized to equal one
b – p-values in paranthesis