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THE DURATION OF UNEMPLOYMENT IN RUSSIA: DOES HIGHER EDUCATION DECREASE UNEMPLOYMENT SPELLS?

Working paper # BSP/2002/058 E

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Вопросы “Кто является безработным?” и “Помогает ли образование найти работу” остаются открытыми даже через десять лет после начала перехода к рыночной экономике. Целью данной работы является определение основных микро и макро факторов, влияющих на вероятность нахождения работы. Также исследуется влияние специализации образования на длительность безработицы.

Основным источником данных в этом исследовании является “Российский Мониторинг Благосостояния и Здоровья Населения” (раунды 5-9). Используя методики анализа длительности, мы оцениваем пропорциональные модели выхода с тремя группами факторов: демографические (возраст, пол, семейный статус), образование (уровень и специализация образования) и региональные (уровень безработицы, средняя зарплата, metropolitan area).

Результаты регрессий показывают, что все три группы факторов значимо влияют на вероятность нахождения работы. Оценки темпов выхода соответствуют теории человеческого капитала, в частности, люди с высшим образованием быстрее находят работу. Кроме того, те, кто поступил в учебное заведение имеют преимущество на рынке труда. Результаты оценивания также показывают, что люди с техническим образованием находятся в лучшем положении. Было также обнаружено гендерное различие во влиянии образования на вероятность нахождения работы.

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Despite transition started ten years ago, the questions “Who are those unemployed?” and “Does education prevent long-term unemployment?” are still open. The aim of this paper is to determine the major micro and macro factors, which influence the probability of finding a job. The influence of the field of education on the duration of unemployment spell is studied as well.

The Russian Longitudinal Monitoring Survey (RLMS) (rounds 5-9) is the basic source for our research. Using duration-data analysis, we estimate proportional hazard models with three groups of factors: demographic (age, gender, marital status), educational (level of education, field of education) and regional (unemployment rate, average wage, metropolitan area).

The results of the regressions show that all the three groups of factors significantly influence the probability of leaving unemployment. The hazard rate estimators are compatible with human capital theory. People with higher education tend to exit unemployment faster than their less educated competitors. It is worth noting that people who entered educational institute after 1985 have higher probability to leave unemployment pool. Estimations reveal that those educated in engineering have better chances to get a job. Gender asymmetries in the influence of marital status, small children, and education on the hazard rates are found.

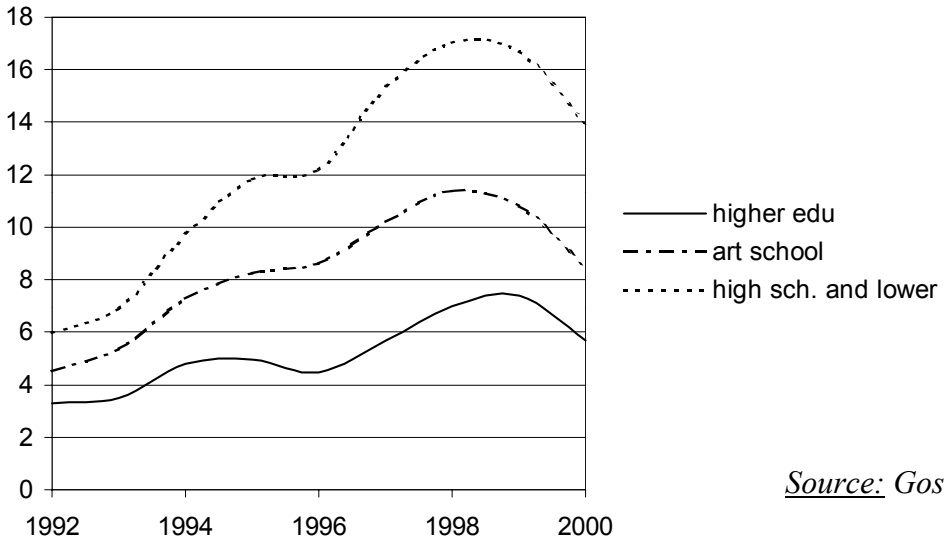
ISBN

Introduction

Transition of the centrally planned economies toward market economies started in early 1990s was accompanied by increase in unemployment. Unemployment rates in almost all Central and Eastern European countries and countries of the former Soviet Union rose up to double digits. And Russia is not the exception, though the uprise was gradual.

It can be expected that a substantial part of unemployment pool in Russia consists of highly educated people, since it is widely accepted that the system of education was heavily distorted in the Soviet Union in the sense that it served the needs of the planned economy, and planning is known to result in huge structural distortions. For example, enormous number of engineers were trained to meet the requirements of military enterprises. A large share of graduates in the economic field specialized in the planned economy and had little knowledge on how market economy operates. Therefore, such specialists became unclaimed when the transition begun since there was little place for them in the market economy. The problem was hardened by sharp decline in output during the transition in Russia. Recession was observed not only in industry, but even more in research and development departments. As a result a substantial part of unemployment pool in Russia could be expected to consist of highly educated people. On the other hand, the conventional wisdom says that more educated have the higher probability of finding appropriate job in comparison with their less educated competitors and they tend to experience shorter unemployment spells. On Figure 1 annual rate of unemployment in different educational groups is presented for years from 1992 to 2000.

Figure 1. Unemployment rate in different educational groups



Source: *Goskomstat*

As can be seen from the graph on Figure1 the highest unemployment rate is observed in the group of those who has only secondary education or lower, and the lowest unemployment rate is among people with higher education. The tendency remains the same during the transition period. It is worth mentioning that the unemployment rate captures both sides of unemployment: the probability of moving from employment to unemployment (incidence rate) and the probability of leaving unemployment pool (duration of unemployment spells). Given that the unemployment rate among highly educated people is the lowest in comparison with other educational groups, the following question arises: "Is it true that those with higher education tend to have shorter spells, or it is rather that the unemployment rate is lower due to lower incidence rate?". The paper focuses on the duration of unemployment spells.

The research attempts to answer the following question: "If once you unemployed, what are your chances to find an appropriate job?" The paper aims to determine the major micro and macro factors[1] that affect the duration of unemployment spells with special focus on education. In particular, we examine the influence of the level and field of education on the probability of finding an appropriate job and hence, on the composition of the unemployment pool. For instance, one of the research questions, which attract attention, is: "whether higher education deter people from falling into long-term unemployment?" In addition we check if there is gender asymmetry in the influence of different factors. We use commonly used (Devine and Kiefer (1991)) duration analysis framework to identify the statistical effect of explanatory variables on the exit rate out of unemployment. We try different specifications of the model.

It is generally argued that the choice of definition of unemployment in a transitional country is a problem. In our paper, we try two definitions of unemployment, namely ILO and "no job" definitions. In contrast to Grogan and van den Berg (2000), we include more explanatory variables, especially those that concern human capital and regional parameters.

The research is based on RLMS database, Rounds V-IX of RLMS (1994-2000). This implies that two more surveys were conducted (in 1998 and in 2000) since the research of Grogan and van den Berg was performed. This additional information allows us to follow the individual during 7 years of the transition and this gives us the opportunity to conduct our study on the larger and more representative sample. The questionnaires of Rounds VIII and IX were improved and expanded in comparison with previous rounds. This gives us the opportunity to include additional explanatory variables, especially those that concern human capital and to test new hypotheses. For example it could be interesting to examine people of which specialization have an advantage of leaving unemployment earlier. Questionnaires of Rounds VIII and IX

[1] We use three groups of factors: demographical, educational and regional characteristics.

contain questions about field of education. This allows including specialization as an explanatory variable.

The paper is organized as follows. Section 1 is devoted to review of the previous literature on the issue. Section 2 is devoted to the discussion of the unemployment definitions and construction of the spells length. In Section 3, the methodology of estimation is described and summary statistics is presented. Section 4 discusses the results of econometric analysis. Conclusions are drawn in Section 5.

Section 1. Review of the related literature

The review will focus on the impact of different factors on the duration of unemployment spells and, in particular, on the influence of education.

There is a considerable amount of empirical research on unemployment duration but these works are mainly based on data from OECD countries (e.g. Park (1997); Kettunen (1997)). Park (1997) obtaines that education has strong effect tending to reduce the probability of long term unemployment in the USA. Kettunen (1997) using Finnish microeconomic data find out that unemployed persons who have about 13-14 years of education have the highest re-employment probability.

It would be interesting to compare our results with the results of similar research on other transitional countries. The direct comparison is not possible since the researchers use different methodologies and data sets of different quality. The brief summary of the impact of education on the probability of leaving unemployment pool in transitional countries is presented in Table 1.

Ham et al (1998) study determinants of unemployment duration in Czech and Slovak republics in 1991-1993 using proportional hazard model. In particular, authors find that married men enjoy shorter unemployment spells than single men in both republics. In Czech republic, only individuals with vocational high school education have relatively higher exit rate. Thus in Slovakia people with only compulsory education have significantly harder time finding a job.

Sorm and Terrel (1997) analyze the question on micro data from Czech republic, years 1994-1996. In contrast to Ham et al (1998), they use multinomial logit model. They find marital status and gender to be not significant except for 1996 when married men had higher probability of re-employment than single men or women (both single and married). With respect to education authors find that education had no significant impact on the spell duration in 1994, though in 1995 - 1996 more educated people had more chances to leave unemployment pool. The authors find negative duration dependence: the longer an individual is unemployed, the more difficulties she has in finding an appropriate job.

Dushi (1997) investigates unemployment in Albania and finds that age, gender, education, local unemployment rate, number of children have no statistically significant effects on the exit rate (only participation in training programs and previous experience matter).

Abraham and Vodopivec (1993) examine major factors affecting the duration of unemployment spells in Slovenia. In their study they use unique data set that describes labor market transitions in Slovenia between 1986 and 1992. The authors find that older workers and least educated workers have the most troubles in finding a job. Unemployed with higher education have significantly higher probability of leaving unemployment pool in comparison with those with only middle school education.

Lubyova and van Ours (1997) examine determinants of unemployment spell duration in Slovakia (1994-1996) using proportional hazard model. They obtain that married men are in better position on the labor market. Authors argue that the probability of finding a job does not depend on age and presence of children.

Lubyova and van Ours (1997) find gender differences in the influence of education: they find that education has significant positive effect on the hazard rate for men but not for women. On the other hand, Jones and Kato (1997) studying Bulgaria 1991-1992 obtain that education has no significant effect for men, while the effect on the exit rate is significantly positive for women. Bellman et al. (1995) using East Germany data support the result of Jones and Kato (1997) on the gender asymmetry in the influence of education.

Micklewright and Nagy (1995) use rich data set to study the factors affecting duration of unemployment spells in Hungary in the period from 1994 to1998. The authors use non-parametric specification of hazard model. It was observed that age and being single have strong negative effect on the chances to find a job for men, but not for women. And it turned out that education significantly positively affects the hazard rate for both males and females.

To summarize, there is no unique trend in the way education affects duration of unemployment spells in transitional countries. But the tendency is as follows: higher education in most cases is likely to lower the probability of longer unemployment spells.

There has not been extensive previous research on unemployment duration in Russia. This fact can probably be explained by the lack of data.

Foley (1997) was the first to analyze determinants of the length of unemployment spells in Russia. He uses Phase I of RLMS (Rounds I-IV, 1992-1994). His sample consists of 1089 unemployed with 57% of the observations being censored. ILO definition of unemployment is applied, and multinomial logit models of transitions from unemployment to employment are estimated controlling for unobserved heterogeneity. It turns out that women tend to have

relatively higher expected duration of unemployment spell and citizens of Moscow and Saint Petersburg have significantly higher probability of finding an appropriate job. Hump-shaped re-employment hazard is identified with respect to unemployment duration. With respect to education Foley find out that the unemployment rate among the higher educated is lower but they have higher duration than the average one.

Grogan and van den Berg (2000) distinguish between four types of unemployment, namely: ILO definition, ”no job” (ILO + people who do not search for a job, but still do want to find it, so-called discouraged workers), ”no work” (“no job”+ people on unpaid leave) and ”no pay” (“no work”+ people who works but have wage arrears). Authors estimate proportional hazard model using RLMS (1994-1996; Rounds V-VII). They consider only those spells, which begin after October 1994 (the date of the first interview). They name an explanatory variable (personal or labor market characteristics) a determinant of the duration of unemployment spell only if it has a similar effect on the length of unemployment for all four definitions of unemployment. It turns out that older people have significantly lower exit rate, and those leaving in Moscow and Saint Petersburg have significantly higher hazard rates than individuals in other areas.

Grogan and van den Berg found that workers with high education have significantly shorter unemployment spells in comparison with lower educated workers. This result is in contrast with the results concerning the effect of education obtained by Foley (1997). Our paper aims to clarify the issue on the basis of more recent information.

Section 2. Data, Definitions of unemployment and Construction of spell length

2.1 Data

Our analysis is based on the second phase of the Russian Longitudinal Monitor Survey (RLMS), a longitudinal panel of around 5000 households across the Russian Federation. It was conducted in the Falls of 1994, 1995,1996,1998, 2000 years (Rounds V-IX).

We use information on individual working history mainly. We restrict our attention to the individuals from the age of 15 to the official retirement age (55 for women and 60 for men). We deal with the spells of unemployment that start after April 1994. In other words, we do not consider spells that began before this date and such sampling allows us to avoid the initial condition problem (Lancaster (1990)).

In the survey individual was asked report whether she were employed and she was asked state the time when the spell began, if the answer was “No”. Individuals are asked to report personal characteristics, such as occupation, age, gender, marital status, education. With respect to education, not only education but also presence of diploma, years of studying, field of education (only for Rounds VIII and IX) and the year of graduation are reported.

The RLMS is a longitudinal survey, so at best we meet the individual only once a year and consequently have the information about elapsed spell duration only at one point in time every year. We attempt to deal with imperfect information as carefully as it possible (for detailed discussion of the spell duration see Section 2.3).

2.2 Definitions of unemployment

In comparison to Grogan and van den Berg, we use only ILO and “no job” definitions of unemployment. Thus we do not consider people on unpaid leave or those who experienced wage arrears as unemployed because it seems that these phenomena were more widespread on the early stages of the transition than on the later stages. Moreover, there are some objections to this approach. In particular, if an individual is employed and experience wage arrears he could not be considered as unemployed as she does not want to change the job. This could be due to the fact that she knows that the situation on the other enterprises is nearly the same (for further details see Earle and Sabirianova (1998)).

2.2.1 ILO definition

It is worth recalling here that ILO definition of unemployment consists of three criteria. To be unemployed according to ILO definition an individual should meet the following requirements. She should be:

- without work
- currently available for work;
- seeking for a job.

Fortunately, data taken from the RLMS allows us to distinguish unemployed individuals of this type. At the beginning of the interview the individual is asked the following question: ”Tell me, please, do you work now, are you on paid or unpaid leave, or do you not work?” And there are five possible answers: “working”, “maternity leave”, “any other paid leave”, “unpaid leave”, “not working”. Therefore, those whose answer was “not working” meet the first

requirement of ILO definition.[2] Then an individual is asked whether she wants to find a job and the possible answers are "yes" and "no". Excluding individuals whose answer was "no", we get the sample of individuals who are without job, but want to find it. The last question of the interview we use here is whether a person was seeking for a job in the last 30 days before the interview. From the sample of those who have no job and want to find it we choose the group of individuals who report "yes" to this question. This completes the construction of the group of ILO unemployed at the date when the survey was conducted. Note that ILO definition is relatively restrictive, especially in terms of application to the transition economies. Table 2 presents annual rates of ILO unemployment based on RLMS and Goskomstat[3]. Rates of ILO unemployment based on RLMS are in line with unemployment rates reported by Goskomstat, though a bit higher.

Table 3 presents annual ILO unemployment rates calculated on RLMS data for different demographical groups[4]. As it can be seen from Table 3, the highest unemployment rate is among young people (aged under 21). This possibly can be explained by the fact that ILO definition allows including students. Moreover, young people usually do not have working experience. It is worth noting that the unemployment rate among highly educated is the lowest in comparison with their less educated competitors. On the other hand the highest unemployment rate is obtained in the group of those who has only high school diploma.[5] It can be noticed from Table 3 that annual unemployment rates in all distinguished groups follow the same time pattern as unemployment rate calculated on the entire sample, e.g. the peak of unemployment is observed in 1998 for each group.

2.2.2 "No job" definition

Under atypical economic conditions of transition to market economy, when labor market is disorganized, the labor absorption is inadequate, self-employment is widespread, ILO (1982) proposed that the definition of unemployment could be relaxed by removing the criterium of seeking for a job. ILO definition is extended by including workers who do not seek for a job, i.e. discouraged workers.

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[2] The important note is that while construction the sample we do not retain all individuals who ever were on maternity leave, as their answers are often inconsistent.

[3] The unemployment rate is calculated as number of ILO unemployed divided by the number of individuals in the labor force.

[4] The unemployment rate in each particular group is computed as number of ILO unemployed in given category divided by the number of economically active individuals in the category.

[5] It is relevant to note here that we consider a person to have a particular level of education only if she has a corresponding diploma. The approach could be viewed as rather restrictive one. Nevertheless it is widely believed that only a diploma is a signal for employer.

To construct the sample of "no job" unemployed we choose those respondents who answer "not working" to the question whether they work and "yes" to the question "Do you want to find work?" Hence, we do not pay attention to the fact of searching for a job. It seems to be important to include individuals who are not seeking for a job into unemployment pool because they constitute a substantial part of non-workers in any considered year. Table 4 presents the percentage of those who did not search for a job in the month before the interview among those who do not work but still wants a job. The intuition behind is that a person who does not search for a job, but still want to find a job can be considered as a person who became discouraged during non-successful search, and can be considered as unemployed.

Table 2 presents annual "no job" unemployment rates calculated on the base of RLMS in different demographical groups[6]. It can be clearly seen from the Table 2 that the "no job" unemployment rate is nearly two times higher than ILO unemployment rate, and follows the same time patter as ILO unemployment rate does.

Rates of "no job" unemployment in demographic groups are introduced in Table 5. According to "no job" definition males are more likely to have a job than females. The extremely high is unemployment rate is obtained in the young people group: it reaches the maximum (76,4%) in 1998. The rate of "no job" unemployment in the group aged from 15 to 21 is three times higher than the unemployment rate in the same group calculated on the base of ILO definition although in other age groups "no job" rate exceeds ILO rate nearly two times. The possible explanation for such a difference is that there is large share of "non-seekers" in this particular age category (75% in 1996). The similar effect is obtained for the group of those who have only high school education. "No job" unemployment rate is much higher in the category of people with only high school education than in other educational categories. As in the case of ILO definition the lowest unemployment rate is obtained in the group of highly educated people.

2.3 Construction of spell length

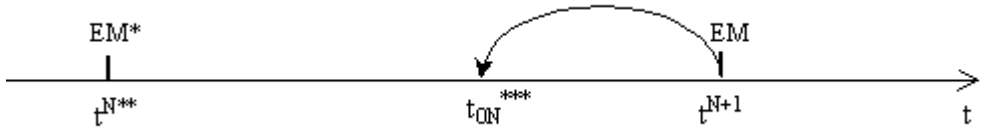
After we have defined whether an individual is unemployed (according to one of two proposed above definitions), we determine the spell duration. The survey is at best conducted only once a year and individuals do not report all labor market transitions that were made during the preceding year. The information about total time spent in the employment (or unemployment) state is absent as well. Instead individuals report the elapsed time of the current spell. Hence, the information is often insufficient to determine the exact moment of relevant transition and we have to deal with unobserved periods. Substantial literature is devoted to the

[6] As in the case of ILO unemployment we compute unemployment rate following standard approach.

methods dealing with imperfect retrospective observation of past events, and some researchs focus on treating yearly surveys (see for example van den Berg (1990b), Magnac and Robin (1994)). The studies lead to the conclusion that, in general, the estimated effects of explanatory variables on exit rate out of unemployment are not heavily biased if one uses simple and reasonable rules to manage unobservable periods. We follow the instruction. Below we present the rules that we used.

Suppose an individual was employed at the time of interview of Round N. Then if the individual is still employed at Round N+1 interview, we consider that she was employed during all the unobserved period. Consequently the information in Round N+1 about elapsed time of employment duration is ignored. We follow this pattern even if employment spell that covers the date of round N+1 begins after the date of Round N interview. See figure 2 (arrow lines denote elapsed time of current spell duration). Hence in the time interval from t^N to t^{N+1} the individual is considered as employed at any moment.

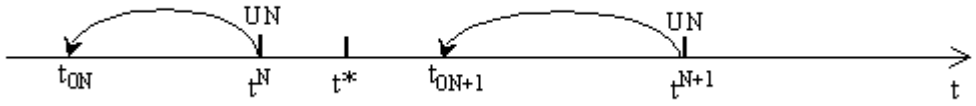
Figure 2



* - *state of an individual: employed (EM) or unemployed (UN)*
** - *the time when the Round N was conducted*
*** - *time when spell began*

Another problem concerns the situation when non-work spell reported in Round N+1 started later than the interview of Round N was conducted. See figure 3.

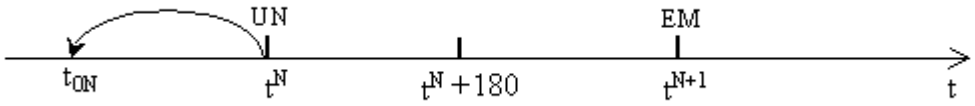
Figure 3



In this case we assume that failure event (finding a job) happens in the middle of unobserved period, i.e. at $t^*=(t_{0N+1}- t^N)/2$. Consequently, a person is considered as employed at any moment in the interval $[t^*; t_{0N+1}]$. And the length of the first unemployment spell is determined as $T=t^*-t_{0N}$.

Assume that in Round N the individual is unemployed, but she is employed in Round N+1. How do we manage the unobserved interval $[t^N; t^{N+1}]$ in this particular case? See figure 4.

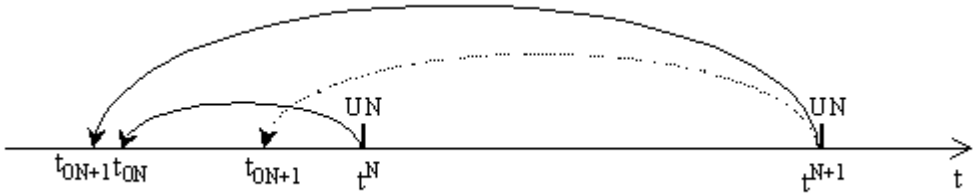
Figure 4



In this case the unemployment spell is assumed to begin at t_{0N} and to end at t^N+180days. Most empirical papers that deal with the similar problems use the "proportional" approach (e.g. Grogan and van den Berg (2000)) in such a situation. According to "proportional" approach, an arbitrarily chosen part x of any unobserved interval is considered as a period of unemployment. But as it was already mentioned we use fixed interval of 180 days to construct the length of non-working spell. The reason for this is that we have two-year gaps between the surveys (the survey was not conducted in 1997 and 1999). So if we treat one-year and two-year unobserved periods in the same way, we get unreasonably higher durations of unemployment spells in period 1996-2000, and this would negatively influence our analysis.

We have to deal not only with unobserved periods. The other problem arises when we face inconsistencies in respondents' answers. The following way of managing inconsistencies is suggested. Assume that an individual is unemployed at two consecutive interviews. Here several situations will be discussed. First, assume that at the interview N+1 individual reports the date when he stopped working and this date do not coincide with the starting date reported in Round N. See figure 5.

Figure 5



It is a common situation when an individual performs the inconsistency in reporting time spent in non-working spell overreporting or underreporting the date when the spell began. In such circumstances we trust the starting date that was reported at the earlier interview (Round N interview in our case). This point is chosen since it is assumed that at the interview that is closer to the starting date individual report this date more accurately (it is not far in the past). Consequently, we suppose that the individual is unemployed at any moment in the interval [$t_{0N;}$ t^{N+1}].

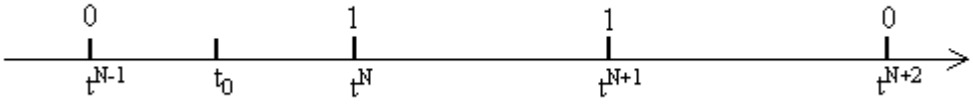
Now suppose that an individual was employed but in the next interview his state changed to unemployed. Here could be inconsistency in reporting the date when non-working spell began. There are observations in our data set that reported elapsed time of the unemployment spell covers the data of previous interview. See figure 6.

Figure 6

We propose the following way to treat this type of inconsistency. Denote $\Delta t=t^N-t_{0N+1}$. If Δt does not exceed 3 months then we take t^N+10days as an approximation of the starting point. But in the case when Δt is greater than 3 months the individual is retained as her answers are not reliable. The intuition here is that we allow the individual to make a mistake, but we do not allow this mistake to make us hesitate whether a person tells the truth.

Furthermore, we control whether an individual wants to find a job (i.e. whether he is in the labor force). Everything is clear in the case when individual was unemployed and in the next interview she reported that she is out of the labor force. We stop to observe the individual as only she comes out of labor force and the corresponding duration is censored. The interesting special instance is when an individual was without work in four consecutive interviews. At the second and at the third interviews she wants to find a job (i.e. she is unemployed on the date of the interview) but at the first and at the last interviews she does not want to find a job. See figure 7. On the figure we put "0"- if individual do not want to find a job and "1" otherwise.

Figure 7



In these circumstances we do not pay attention to the reported elapsed time of non-working spell, because it usually includes the time, when the individual was out of labor force. The rule applied here is rather simple. Denote $t_0=(t^N-t^{N-1})/2$. Therefore the length of the unemployment spell is $T=t^{N+1}-t_0$. This spell is considered as censored.[7]

To summarize, we have 642 non-censored and 1184 censored observations for ILO definition of unemployment, for "no job" definition these numbers are 1043 and 1774, xorrespondingly.

[7] Recall that we ignore spells that began before April 1994 to avoid initial condition problem. We have right-censored observations if we do not have more information about the individual or she fell out of the labor force.

Section 3. Methodology of estimation

3.1 What is hazard function?

In analyzing the duration of unemployment spells and the impact of education on the duration of unemployment spells we use hazard model. For our purpose it is sufficient to consider a model where individuals are assumed to have only two states, employment and unemployment. The failure event is the transition from unemployment to employment. Note that we treat both non-censored and right-censored observations. Let us denote the duration of spell as T and let it be random. Then $F(t)=Pr(T<t)$ –cumulative distribution function. The probability that unemployment spell lasts longer than t is called survival function $S(t)$:

$S(T)=1-F(T)=Pr(T\geq t)$.

As we examine the probability of leaving unemployment to employment at time t as a function of various characteristics, the hazard function is particularly useful:

$$\lambda(t)=\lim_{t\to 0} Pr(t\leq T<t+h \mid T\geq t)/h=f(t)/S(t),$$

$$where\ f(t)=dF(t)/dt$$

Hazard function $\lambda(t)$ can be interpreted as the rate at which spells will be completed at duration t, given that they last till t. Positive duration dependence implies that $d\lambda(t)/dt>0$ and it means that the probability that a spell will end shortly increases as the spell increases at length. Negative duration ($d\lambda(t)/dt<0$) means in our case that with time the probability of leaving to employment falls. The integrated hazard $\Lambda(t)=\int \lambda(u)du$ is also useful. The relation to the survival function is $S(T)=exp[-\Lambda(t)]$. As $F(t)$ usually exponential, Weibull and log-logistic cumulative distribution function are used (see Kiefer(1988)). We try both Weibull and log-logistic distributions.

3.2 Estimation

Note that explanatory variables can affect the distribution of the unemployment duration in many ways. The most commonly used pattern is proportional hazard specification. This specification is very popular as it is rather simple in the coefficient interpretation: for example, if the coefficient at the regressor x is equal 2, it means that a one-unit change in x doubles the hazard of finding a job. It also should be mentioned here that the sign of the coefficient indicates the direction of the effect of the explanatory variable on the hazard rate. To formalize, in the case of proportional hazard framework hazard function is defined as follows:

$\lambda(t,x,\beta,\lambda_0)=\varphi(x,\beta)\lambda_0(t)$, where

- $\varphi(x,\beta)=exp(\Sigma\beta_i x_i)$, $\{x_i\}$-explanatory variables (personal characteristics, characteristics of unemployment compensation system, etc)
- $\lambda_0(t)\ )=\alpha t^{\alpha-1}$ if we use Weibull distribution to determine a baseline hazard
- $\lambda_0(t)\ )=\alpha t^{\alpha-1}/(1+t^{\alpha})$ if we use log-logistic specification

We estimate two separate equations. The first one is to determine the effects of demographical factors, regional characteristics and level of education on the hazard ratio. In this case hazard function is defined as follows:

$$\lambda(t,x,\beta,\lambda_0)=\lambda_0(t)exp(\beta_0+\beta_1 age+\beta_2 age^2+\beta_3 brak+\beta_4 baby+\beta_5 edu_1+\beta_6 edu_2+\beta_7 edu_3+ \quad (1)$$
$$+\beta_8 edu_4++\beta_9 lune+\beta_{10} exper),$$ where

age – age of individual in years, age^2 – age squared, *brak* - dummy of marital status (is equal to 1 if married, including common law), *baby* – number of children under 7 years old; edu_i (i=1, 2, 3, 4) – dummies for the highest attained level of education: edu_1 - professional courses or PTU, FZU without secondary education, edu_2 - PTU, FZU with secondary education, edu_3 – technical art school , edu_4 - institute/university; *exper* – dummy for having more than a year of working experience; *lune* – logarithm of local unemployment rate.

The second equation mainly focuses on the effects of the field of education:

$$\lambda(t,x,\beta,\lambda_0)=\lambda_0(t)exp(\beta_0+\beta_1 age+\beta_2 age^2+\beta_3 brak+\beta_4 baby+\beta_5 tech+\beta_6 med+\beta_7 teach+ \quad (2)$$
$$+\beta_8 admin+\beta_9 tech*edu_4+\beta_{10} med*edu_4+\beta_{11} teach*edu_4+\beta_{12} admin*edu_4+\beta_{13} lune+$$
$$+\beta_{14} exper),$$ where

tech, med, teach, admin are dummies for the field of the education: engineering, healthcare, teaching and administration correspondingly.

3.3 Summary statistics

In this section we present summary statistics for the used variables used. Means of variables (taken at the beginning of the unemployment spell), which are supposed to affect the duration of unemployment spell, are presented in the Table 6.

Firstly, as seen from Table 6 there is no great difference in means of variables for ILO and "no job" unemployment: average age of unemployed is 32 and approximately 65% of unemployed are married. To control for the effect of the experience, we use dummy of previous employment, which is equal to1, if a person has more than a year of working experience. It turns out that males and females do not differ greatly in terms of previous employment history; approximately 90% have worked before. To capture demographic effects, we use measure of age, number of small children and marital status dummy (married including the common law marriages equal 1). It can be inferred from Table 6 that age is quite similar for men and women,

although unemployed men tend to be nearly 1 year older than unemployed women. Higher proportion of women are married.

To identify the impact of education we use two groups of dummies: four dummies for the highest attained level of education and four dummies for the field of education. Hence it can be concluded that relatively more women attained art school education although a higher proportion of men attained only professional courses or PTU, FZU without secondary education. Other education levels are similar for men and women. Although the numbers seem to be comparable for both definitions of unemployment, the proportion of "no job" unemployed who attained only high school is higher in comparison with the similar fraction among ILO-unemployed.

We restrict our attention to the four fields of education: engineering, teaching, administration and healthcare. As a result we have four dummies, each of them equals 1 if an individual has the corresponding level of education. Summary statistics on these dummies are reported in Table 6. It can be inferred that in comparison with women relatively more men have education in the field of engineering. Hence there are considerably more women specialized in the fields of healthcare, teaching and administration. The proportions are similar for ILO and "no job" unemployed.

In Table 7 survival time summary statistics are presented. It turns out that median "no job" unemployment spell lasts 2.18 years and median ILO unemployment spell lasts 1.48 years. This noticable difference in median durations for two definitions can be explained as follows. In comparison with "no job" unemployed ILO unemployed are active searches, i.e. they apply efforts looking for a job. So it seems that the strategy of active search is beneficial and as a consequence ILO unemployed have lower median duration. As is seen from Table 7 males enjoy shorter median spell duration than females. Calculations of median durations for different age and educational groups show that individuals aged from15 to 21 have the shortest median spell, while individuals aged 40-49 tend to stay in unemployment longer than others. Comparison of different educational groups shows that those with general secondary education and lower have the longest median unemployment spell duration. On the other hand, highly educated people enjoy the shortest spells. Those with education in the field of teaching have shorter unemployment spells in comparison with doctors, engineers and administrators. Higher education tends to reduce the duration of unemployment spell of doctors and teachers, but for engineers and administrators the effect seems to be negligible. It is worth noting that tendencies are similar for both definitions of unemployment.

Section 4. Results.

In this section the results of estimating hazard function for males and females are discussed. We analyze the effects of explanatory variables on the hazard rate with the focus on the impact of education. Gender differences are discussed as well. Equations are estimated separately for males and females. We estimate proportional hazard model for two samples: sample of ILO unemployed and the sample of "no job" unemployed. We try Weibull and log-logistic specifications of the model. It is worth noting that both specifications provide close estimates of coefficients.

Firstly, to identify the influence of different demographical, regional characteristics and the level of education we estimate proportional hazard model with the hazard function defined as (1) (see Section 3.2). The results of estimation are presented in Table 8 for the sample of ILO unemployed and in Table 9 for the sample of "no job" unemployed.

Our estimation yields a number of interesting results with respect to influence of demographic variables. The obtained effects are qualitatively similar for both samples. We find that age has negative effect on the probability of leaving unemployment for both men and women. This conclusion coincides with the standard human capital theory. The duration effect of age is, however, smaller for women: every additional year decreases this probability by 4% for males[8] and only by 2% for females. Marital status has opposite effects for men and women. Married men have higher probability of finding a job in comparison with single men. The intuition for the result is that married men are usually breadwinners in their families and they have to search for a job actively. Moreover, it seems that they take any job offer that provides living for the family. In other words, marriage decreases reservation wage for men. Married women tend to stay longer in unemployment than single ones. In contrast with males, marriage seems to have positive effect on the reservation wage of a woman as her husband's wage can be considered as a non-labor income.

We find that the length of unemployment spell for women increases with the increase in number of small children. This can be explained by the fact that small children need permanent care and many women prefer to take care of their children themselves and they tend to look for part time jobs or jobs at home. The supply of the jobs of these kinds is limited, however. On the other hand, employers are known to prefer not to hire women with small children, as they are likely to have lower productivity. To illustrate this point: a woman with two children has 28% lower chances to find an appropriate job in comparison with a woman who has only one baby (for ILO unemployed woman). The effect is slightly lower for "no job" unemployed females –

21%. The effect of having small children for men is positive but the level of significance is only about 15%.

Individuals with more than one year of working experience have higher chances to find a job than their more experienced competitors. The effect is stronger for males.

We control for local unemployment rate to capture the effect of local labor market conditions. As it was expected the probability of finding a job adversely related to the rate of local unemployment.

We find substantial gender asymmetry. With respect to the impact of the level of education on the duration of unemployment spells. Males with professional courses or PTU without secondary education certificate enjoy higher exit rate in comparison with those who have only high school diploma, while the effect is insignificant for females. It seems that it is important for men to have specific skills: a man who has diploma of this particular type have nearly 30% higher probability of leaving unemployment pool than a man with only secondary education. Furthermore, it is widely believed that there are relatively more jobs for low educated males than for low educated females.

There is no gender asymmetry in the impact of higher education, it increases the probability of finding a job by 50% both for males and females and the effect is similar for both definitions of unemployment. Our results on the higher education support the findings reported by Grogan and van den Berg (2000). The result (as compared with Foley (1997)) could reflect the fact that the educational system began to adjust to the needs of emerging market economy. In other words it seems that not only labor market situation changes, but also the higher education itself experiences structural transformations.

To examine the effect of the field of education, we estimate proportional hazard model with the hazard function specified as (2) (see Section 3.2). The results of estimation are presented in Table 10 for the sample of ILO unemployed and in Table 11 for the sample of "no job" unemployed. We analyze the impact of four fields of education: engineering, teaching, healthcare and administration (the reference category is working specialities).[9] Again obtained effects tend to be qualitatively similar for both samples.

We find that there is no significant effect of the field of education for men. In contrast, women who were trained in the fields of engineering and administration tend to have higher hazard rates than those with workers' specialties. The influence of education in healthcare and

[8] All the numbers will be given for Weibull specification

9 It is worth noting that the distinguished categories mainly consist of those with completed higher education and those with technical art school diploma.

teaching is insignificant, however. We also find that women with higher education in the field of engineering and administration and women with only technical art school education appear to have equal the chances to find an appropriate job. Hence, the level of education does not matter for female engineers and administrators. At the same time, it was found that female doctors with higher education have approximately three times (for ILO unemployed) higher probability of finding a job in comparison with those who attained only art school education. The effect is even stronger for the sample of "no job" unemployed. The same effect is obtained for women with education in the field of teaching: female teachers with higher education tend to leave unemployment pool earlier in comparison with art school graduates.

Section 5. Conclusions

In this paper we analyze the determinants of unemployment in Russia. We evaluated the influence of three groups of variables: demographic, regional and educational parameters on unemployment duration. Using RLMS we distinguish two types of unemployed and estimate the duration models for each type. Estimations are done separately for males and females. In addition, for each type, we estimate model using different specification.

With respect to demographic characteristics, older individuals are less likely to find a job. Married men enjoy shorter unemployment durations than single ones, while married females tend to have longer unemployment spells. Women with small children are less likely to leave the unemployment pool.

The impact of education on the duration of unemployment spells is in the focus of our study. We find important educational effects on the probability of finding a job. It turns out that individuals with higher education are more likely to get employed. The effect of higher education is similar for both males and females. University degree increases the probability to find an appropriate job by 50%. Therefore, our analysis leads to the conclusion that those with higher education are in better position on the transitional labor market.

It turns out that there are substantial gender asymmetries in the impact of the education on the probability of finding a job. Men with certificate on professional courses or PTU without secondary education tend to have shorter spells than those with only secondary education, while the effect is insignificant for females.

Analyzing the effects of the fields of education we find no significant effect for men. Women educated in the field of engineering and administration tend to have higher hazard rates

in comparison with teachers and health workers. Higher education has positive duration effect for female doctors and teachers.

It turns out that the duration effects are qualitatively very similar across different types of unemployment and model specifications.

Our analysis provides useful information for the design of labor market policies that aims to reduce the proportion of long term unemployed. The research allows identification of the general characteristics (in particular, age, education, gender, etc) of those who are likely to be long-term unemployed, as well as those, who have less difficulties in finding a new job. In this way, the research can help to mark out the targeting group, i.e. the group of those who are expected to become long-term-unemployed and as a consequence who have higher probability of falling into poverty. Correspondingly the work helps to determine what levels and what fields of education are well-matched to transition economy. The results on the influence of the field of education could possibly provide the base for creating effective retraining programs.

Table 1. Effect of educational level on the probability of finding a job in transitional countries

Paper	Data	Methodology of estimation	Effect of education on the probability to find the job
Ham et al (1998)	Slovakia (1991-1993)	Hazard model	Unemployed with only a compulsory education (8 years) has a significantly lower probability of finding a job than individuals with secondary and university education
	Czech Republic (1991-1993)	Hazard model	Only individuals with vocational high school education have the advantage in finding a job
Sorm, Terrel (1997)	Czech Republic (1994-1996)	Multinomial logit models	In 1994 no significant effect In 1995-96 more educated have a higher probability to find the job
Lubyova and van Ours (1997a)	Slovakia (1994-1996)	Proportional hazard model	Significant positive effect for men, but not for women
Bellmann et al. (1995)	East Germany (1990)	Multinomial logit models	For men no significant effect For women significant positive effect
Abraham, Vodopivec (1993)	Slovenia (1986-1992)	Hazard model	Least educated have the most problems in finding a job Unemployed with higher education have a higher probability to exit the unemployment than those with only middle school education
Micklewright, Nagy (1995)	Hungary (1994-1998)	Non parametric hazard model	Positive effect on the exit hazard
Jones, Kato (1997)	Bulgaria (1991-1992)	Multinomial and binomial logit models	For men no significant effect For women significant positive effect
Dushi (1997)	Albania	Hazard model	No significant effect

Table 2. Unemployment rate in 1994-2000

Year	1994	1995	1996	1998	2000
Rate of "general" unemployment*	**8,1**	**9,5**	**9,7**	**13,3**	**10,5**
Rate of ILO unemployment**	**9,7**	**10,8**	**11,7**	**13,6**	**11,3**
Rate of "no job" unemployment**	**22,1**	**22,3**	**29,4**	**27,9**	**26,1**

*Note: *- reported by Goskomstat*
*** - authors' calculations based on RLMS (Rounds V-IX)*
Source: RLMS (1994-2000)

Category		Unemployment rate in category				
		1994	**1995**	**1996**	**1998**	**2000**
Gender	Females	10,4	11,7	11,7	12,4	10,8
	Males	9,0	9,8	11,6	13,6	11,8

Table 3. ILO unemployment in different demographical groups

Age	Under 21	**22,3**	**24,7**	**25,1**	**26,8**	**21,0**
	21-29	13,1	13,5	14,9	15,2	13,4
	30-39	7,6	9,1	9,5	12,2	10,2
	40-49	6,6	6,9	8,3	9,4	9,3
	50-59	5,7	8,1	8,6	8,6	6,8
Education level	Professional courses or PTU, FZU without secondary education	10,9	10,8	10,6	14,3	11,1
	High school	12,9	14,7	18,7	19,4	16,9
	PTU, FZU with secondary education	9,7	12,2	12,3	12,7	10,5
	Technical/medical art school	8,2	8,5	9,9	12,0	11,1
	Institute/university	**6,3**	**6,8**	**6,9**	**7,9**	**7,2**

Source: RLMS (1994-2000)

Table 4. Percentage of non-workers who did not search for a job in the month before the interview

Year	1994	1995	1996	1998	2000
% of "non-seekers" among jobless	54	50	51	52	53

Source: RLMS (1994-2000)

Table 5. "No job" unemployment in different demographical groups

Category		Unemployed as percentage of individuals in group				
		1994	**1995**	**1996**	**1998**	**2000**
Gender	Females	24,5	25,0	26,4	28,8	27,5
	Males	19,8	19,8	23,4	27,1	24,6
Age	Under 21	**68,7**	**66,7**	**71,7**	**76,4**	**70,6**
	21-29	24,7	24,8	28,9	30,8	26,7
	30-39	15,9	16,5	17,9	23,0	21,3
	40-49	12,7	13,7	15,6	18,3	18,5
	50-59	16,0	16,8	18,9	20,1	17,8
Education level	Professional courses or PTU, FZU without secondary education	20,4	19,3	23,2	28,4	25,4
	High school	37,8	38,5	49,1	53,1	53,6
	PTU, FZU with secondary education	20,0	21,4	23,5	27,9	22,8
	Technical/medical art school	16,8	16,8	17,6	20.2	20,2
	Institute/university	**11,0**	**11,5**	**11,3**	**14,3**	**12,7**

Source: RLMS (1994-2000)

Table 6. Means of variables (at the beginning of unemployment spell)

	ILO unemployed			"no job" unemployed		
	Males	**Females**	**Total**	**Males**	**Females**	**Total**
No of observations	954	872	1826	1418	1453	2871
Age (in years)	33,0	31,5	32,2	33,0	31,2	32,1
Married (incl. com. law)	0,63	0,66	0,65	0,61	0,64	0,63
Number of children not older than 7	0,31	0,34	0,32	0,31	0,36	0,34
Professional courses or PTU, FZU without secondary education	0,25	0,14	0,20	0,24	0,14	0,19
High school	0,28	0,27	0,28	0,32	0,35	0,32
PTU, FZU with secondary education	0,21	0,17	0,19	0,20	0,18	0,19
Technical/medical art school	0,15	0,29	0,22	0,13	0,25	0,19
Institute/university	0,11	0,12	0,11	0,11	0,10	0,10
Tech (field: engineering)	0,16	0,13	0,15	0,15	0,10	0,12
Med (field: healthcare)	0,01	0,05	0,03	0,01	0,06	0,03
Teach (field: teaching)	0,04	0,10	0,7	0,01	0,06	0,03
Cler(field: administration)	0,01	0,07	0,04	0,03	0,10	0,04
Previously employed	0,94	0,91	0,93	0,92	0,90	0,91

Source: RLMS (1994-2000)

Table 7. Survival time summary statistics: total sample; gender, age and educational groups

	ILO unemployed		"no job" unemployed	
	Number of subjects	**Median survival time (years)**	**Number of subjects**	**Median survival time (years)**
Total sample	1826	1,49	2817	2,18
Males	954	1,42	1418	1,82
Females	872	1,54	1453	2,61
Under 21	368	1,01	697	1,65
21-29	510	1,51	785	1,84
30-39	458	1,29	647	1,72
40-49	359	1,53	561	2,56
50-59	174	·	309	·
Professional courses or PTU, FZU without secondary education	371	1,30	548	2,17
High school	508	1,80	990	2,51
PTU, FZU with secondary education	349	1,48	549	2,05
Technical/medical art school	409	1,47	546	1,93
Institute/university	223	1,10	312	1,49
Engineering	261 (96)*	1,21 (1,21)*	339 (119)*	1,72 (1,69)*
Medicine	59(14)	1,23 (1,14)	94 (25)	2,18 (1,14)
Teaching	68(29)	1,32 (0,75)	98 (40)	1,59 (0,78)
Administration	126(39)	0,94 (0,94)	194 (60)	2,02 (2,01)

**-in parentheses number of subjects/median duration among highly educated subgroup in each group*
Source: RLMS (1994-2000)

Table 8. Estimation of proportional hazard models for the sample of ILO unemployed, specification (1).

Explanatory variable	β coefficients			
	Weibull model (AFT[10] specification)		Loglogistic model (AFT specification)	
	Females	Males	Females	Males
Age	-0.021*** [2.92]	-0.033*** [5.71]	0.011** [2.27]	0.020*** [5.24]
Married	-0.198* [1.63]	0.510*** [3.86]	0.111 [1.12]	-0.345*** [3.87]
Number of children under 7 y.o.	-0.329*** [2.75]	0.057 [0.63]	0.153* [1.83]	-0.024 [0.39]
Professional courses or PTU, FZU without secondary education	0.221 [1.07]	0.444*** [2.72]	-0.138 [0.95]	-0.338*** [3.17]
PTU, FZU with secondary education	0.165 [0.86]	0.285 [1.13]	-0.150 [1.10]	-0.166 [1.53]
Technical/medical art school	0.255 [1.50]	0.267 [1.46]	-0.195 [1.63]	-0.287** [2.34]
Institute/university	0.439** [2.17]	0.448** [2.35]	-0.310** [2.11]	-0.359*** [2.76]
Regional unemployment rate	-0.666*** [3.84]	-1.258*** [7.79]	0.651*** [4.69]	0.971*** [8.60]
Previously employed	0.584** [2.14]	0.637** [1.99]	-0.372** [2.09]	-0.378** [1.99]
Constant	0.549 [1.09]	1.842*** [3.68]	-1.092*** [2.88]	-1.869*** [5.85]

[10] Accelerated failure time specification

Gamma			0.523 (0.024)^	0.488 (0.020)^
P parameter	1.326 (.054)^	1.338 (0.048)^		
Log Likelihood	-639.74	-727.94	-602.55	-672.05
Number of subjects	872	954	872	954
Number of failures	289	353	289	353

Note: t-statistics in the parenthesis
**- significant at 10% level*
***- significant at 5% level*
****- significant at 1% level*
^ - standard error in parenthesis
Source: RLMS (1994-2000)

Table 9. Estimation of proportional hazard models for the sample of "no job" unemployed, specification (1).

Explanatory variable	β coefficients			
	Weibull model (AFT specification)		Loglogistic model (AFT specification)	
	Females	Males	Females	Males
Age	- 0.019** [1.96]	-0.034*** [7.19]	0.021*** [3.22]	0.023*** [6.78]
Married	-0.309*** [3.00]	0.276** [2.53]	0.258*** [2.80]	-0.272*** [3.26]
Number of children under 7 y.o.	-0.241*** [2.89]	0.100 [1.45]	0.156** [2.26]	-0.041 [0.77]
Professional courses or PTU, FZU without secondary education	-0.026 [0.16]	0.259** [2.04]	0.071 [0.54]	-0.259*** [2.66]
PTU, FZU with secondary education	0.023 [0.16]	0.127 [1.00]	-0.051 [0.42]	-0.097 [0.99]
Technical/medical art school	0.118 [0.88]	0.266 [1.20]	-0.103 [0.89]	-0.228** [1.99]
Institute/university	0.405** [2.39]	0.417*** [2.64]	-0.328** [2.28]	-0.300** [2.44]
Regional unemployment rate	-0.562*** [3.97]	-1.131*** [8.89]	0.617*** [4.87]	1.069*** [10.28]
Previously employed	0.776*** [3.63]	1.021*** [4.40]	-0.570*** [3.39]	-0.656*** [3.87]
Constant	-1.279** [2.18]	1.269*** [3.35]	0.866* [1.70]	-1.860*** [6.20]

Gamma			.645 (0.023)^	0.571 (0.019)^
P parameter	1.169 (0.039)^	1.213 (0.037)^		
Log Likelihood	-1156.24	-1219.78	-1113.83	-1150.79
Number of subjects	1453	1418	1453	1418
Number of failures	485	558	485	558

Note: t-statistics in the parenthesis
**- significant at 10% level*
***- significant at 5% level*
****- significant at 1% level*
^ - standard error in parenthesis
Source: RLMS (1994-2000)

Table 10. Estimation of proportional hazard models for the sample of ILO unemployed, specification (2).

Explanatory variable	β coefficients			
	Weibull model (AFT specification)		Loglogistic model (AFT specification)	
	Females	Males	Females	Males
Age	-0.022*** [3.04]	-0.029*** [5.10]	0.010** [2.18]	0.018*** [4.81]
Married	-0.186 [1.32]	0.537*** [4.05]	0.115 [1.18]	-0.389*** [4.36]
Number of children under 7 y.o.	-0.303** [2.54]	0.081 [0.91]	0.149* [1.79]	-0.025 [0.40]
Tech	0.445** [2.18]	-0.042 [0.24]	-0.394*** [2.68]	-0.084 [0.71]
Med	0.400 [1.47]	0.676 [1.16]	-0.149 [0.80]	-0.190 [0.51]
Teach	-0.396 [1.30]	0.631 [1.08]	0.006 [0.03]	-0.227 [0.55]
Admin	0.435** [2.18]	0.043 [0.09]	-0.249* [1.76]	-0.246 [0.81]
Tech*edu4	-0.173 [0.54]	0.131 [0.51]	0.310 [1.35]	-0.033 [0.19]
Med* edu4	0.911* [1.73]	-0.928 [1.12]	-0.495 [1.17]	0.297 [0.55]
Teach* edu4	1.080*** [2.72]	-0.192 [0.21]	-0.477 [1.59]	-0.368 [0.54]

Adm*edu4	-0.695 [1.55]	0.260 [0.46]	0.170 [0.50]	-0.167 [0.43]
Regional unemployment rate	-0.755*** [4.30]	-1.306*** [7.95]	0.680*** [4.89]	0.968*** [8.52]
Previously employed	0.667** [2.45]	0.688** [2.15]	-0.384** [2.17]	-0.418** [2.21]
Constant	0.761 [1.53]	2.002*** [3.98]	-1.187*** [3.16]	-1.918*** [5.98]
Gamma			.524 (0.024)^	.490 (0.020)^
P parameter	1.353 (0.056)^	1.339 (0.049)^		
Log Likelihood	-632.11	-730.66	-597.89	-675.74
Number of subjects	872	954	872	954
Number of failures	289	353	289	353

Note: t-statistics in the parenthesis
**- significant at 10% level*
***- significant at 5% level*
****- significant at 1% level*
^ - standard error in parenthesis
Source: RLMS (1994-2000)

Table 11. Estimation of proportional hazard models for the sample of "no job" unemployed, specification (1).

Explanatory variable	β coefficients			
	Weibull model (AFT specification)		Loglogistic model (AFT specification)	
	Females	Males	Females	Males
Age	0.073** [2.14]	-0.031*** [6.80]	-0.092*** [3.24]	0.021*** [6.29]
Age^2	-0.001*** [2.93]		0.002*** [3.82]	
Married	-0.333*** [3.20]	0.307*** [2.81]	0.274*** [2.99]	-0.307*** [3.70]
Number of children under 7 y.o.	-0.232*** [2.77]	0.108 [1.56]	0.148** [2.15]	-0.046 [0.85]
Tech	0.547*** [3.39]	0.099 [0.69]	-0.488*** [3.29]	-0.082 [0.72]
Med	-0.027 [0.13]	0.345 [0.68]	0.073 [0.37]	-0.233 [0.62]
Teach	-0.042 [0.18]	-0.261 [0.45]	-0.035 [0.17]	0.142 [0.30]
Admin	0.253* [1.80]	-0.323 [0.72]	-0.234* [1.68]	0.146 [0.43]
Tech*edu4	-0.080 [0.28]	0.099 [0.46]	0.182 [0.73]	-0.014 [0.08]
Med* edu4	1.380*** [2.76]	-0.348 [0.49]	-0.992** [2.44]	0.329 [0.62]

Teach* edu4	0.957*** [2.98]	0.949 [1.04]	-0.673** [2.36]	-0.689 [0.95]
Adm*edu4	-0.381 [1.17]	0.552 [1.03]	0.273 [0.95]	-0.525 [1.27]
Regional unemployment rate	-0.583*** [4.09]	-1.123*** [8.77]	0.657*** [5.19]	1.064*** [10.16]
Previously employed	0.827*** [3.88]	1.047*** [4.53]	-0.579*** [3.45]	-0.694*** [4.13]
Constant	-1.338** [2.31]	1.250*** [3.29]	0.756 [1.50]	-1.847*** [6.11]
Gamma			.639 (0.023)^	0.573 (0.019)^
P parameter	1.180 (0.04)^	1.211 (0.037)^		
Log Likelihood	-1144.79	-1222.05	-1104.06	-1153.58
Number of subjects	1453	1418	1453	1418
Number of failures	485	558	485	558

Note: t-statistics in the parenthesis
**- significant at 10% level*
***- significant at 5% level*
****- significant at 1% level*
^ - standard error in parenthesis
Source: RLMS (1994-2000)

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