EVALUATION OF ACTIVE LABOUR
MARKET POLICIES IN UKRAINE
USING MICRO LEVEL REGISTRY
DATA

by

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Abstract

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This study is aimed to evaluate efficiency of Active Labor Market Policies in Ukraine, namely efficiency of training program and public works program using micro level registry data from Kyiv employment center during years 2000-2003. The results of the duration data analysis show that participation in the training has positive effect on the transition from the unemployment to employment, while participation in public works program has no effect on the duration of the unemployment or even prolongs unemployment in some specifications. The application of logit analysis with the Heckman two-stage selectivity correction to the data supports conclusions obtained from duration data analysis. The proposed way to increase effect of public works may be in increasing the quantity and the quality of possible jobs which can be attended through public works program. In addition, the minimum time for participation in public works should be extended. Also, impact of training may be increased if the enrolment of unemployed individuals of near pension age will decrease.

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LIST OF ABBREVIATIONS

ALMP	Active Labor Market Policy
PLMP	Passive Labor Market Policy
ILO	International Labor Organization
PEC	Public Employment Center

Chapter 1

INTRODUCTION

In Ukraine, as in many other countries, the process of transition from the planned to the market economy reduced employment and standards of living of the most part of the population. The recession of the economy was long, abysmal and destructive. Large and small enterprises or whole industries shut down and thousands of workers lost their jobs every week. Moreover, unemployed people could not find new jobs for some months or years. Sometimes the unemployment situation in Ukraine looked very similar to the situation in the USA during the Great Depression when people were starving, diseased, and demoralised. To ensure survival many city-dwellers got small land parcels near city and cultivated vegetables and fruits on them. A lot of workers accepted tremendous wage arrears, unpaid leave, and wage reductions just to keep their jobs.

Under such conditions the government was forced to reduce unemployment and increase incomes of the population by any means. One kind of measures that the government applied was Active Labour Market Policy (ALMP). Among different types of ALMP, which the government implemented, were training and retraining of unemployed, intervention (subsidised) work, public work, consulting services, loans and grants to support small business start-ups, services to reduce unemployment of young people, and assistance for disabled. In spite of these policies and recent economic growth in Ukraine that reduced the unemployment rate, in many regions of the country the problem of excess unemployment remains unsolved. Also, it stays unclear which of the policies made the greater contribution to the unemployment reduction and which of them were ineffective.

Because of these unsolved problems and because of little micro level research in this area for the case of Ukraine, it is important to evaluate Active Labour

Market Policy in Ukraine. Particularly, I will focus on the efficiency of training and retraining of unemployed, and public works in reducing registered unemployment.

In general, it is possible to have a "selection" problem in this type of research. In simple words, the effects from some kind of ALMP may appear not because the program has any effect, but rather because people who are chosen for participation have better opportunities than other. For, example these people could be better educated or are younger than the rest. To overcome this "selection" trap, investigations employ different econometric techniques. For example, it is possible to use the Heckman two-stage selectivity correction technique to estimate and correct possible biases of the estimates for the efficiency of an ALMP due to difference in the characteristics of individuals from control and treatment groups. For instance, only better able individuals with higher motivation may participate in some program, or vice versa worse individuals may be attracted to the ALMP. So, this selection problem can generate either upward or downward biases in the estimated effects of the ALMP and the directions of these biases are difficult to predict in advance. The other possible technique is evaluation of the impact of an ALMP on duration of the unemployment spell using methods of transition data analysis and controlling for differences in individual characteristics of the participants. I plan to use both methods in my study to obtain conclusions which will not depend on the assumptions of particular methodology.

Chapter 2

LITERATURE REVIEW

In the last decade of the 20th century unemployment received a lot of attention. A wide variety of theoretical and empirical studies attempted to analyse unemployment from different points of view: its causes and consequences, its relationships with other economic and social phenomena, its 'victims' (people who are affected the most by the unemployment) and the policies to reduce its extent. From the last trend of studies one can distinguish studies that concerned Active Labour Market Policy and Passive Labour Market Policy. ALMP consisted mainly of measures which change labour force characteristics. In opposite, PLMP provided financial assistance for the unemployed people while they are looking for new jobs. Both these policies are usually financed from the public funds, but private training programs for unemployed also exist. As public funds are scarce, a rigorous evaluation of the effectiveness of the employment measures is important.

For OECD countries a sizeable collection of articles concerning this topic has been produced. A recent review of this literature can be found in Lehmann (1995), Heckman et al. (1999), and Martin and Grubb (2001). From these studies conclusions about efficiency of different ALMP and appropriateness of various methods of program evaluation can be drawn.

In general, according to Martin and Grubb (2001), spending on labour market policies in OECD countries varied substantially across countries and throughout time. Not surprisingly, the spending increased for countries with greater rate of unemployment and for periods when unemployment enlarged. Also, the set of particular measures in ALMP changed in different states; however, the five main kinds of ALMP are very similar. They are the following: labour market training, youth measures, subsidised employment, employment services, and assistance for the disabled. Labour market training is primarily educational program for unemployed adults which is conducted to give them some other profession or increase their skills in their profession. Youth measures are directed toward school-leavers and their main purpose is to give this special category of unemployed additional education or apprenticeship training to increase their labour-market skills. Subsidised employment is ALMP through which employment offices create extra workplaces for the unemployed. This policy uses three main methods: the creation of jobs in the public sector, subsidy payments for private firms who take additional unemployed; and grants and loans for own business start-up. Employment services consist of consultations, job placements, searching in databases for available workplaces, administration of the unemployment benefits, counselling for training programs etc. At last, assistance for the disabled is aimed to employ this category of jobless using vocational training or creation of special workplaces for disabled.

Conclusions about the effectiveness of Active Labour Market Policies can be found in the same source (Martin and Grubb (2001)). Overall, results of many ALMP were not substantially large and varied throughout different types of programs. For example, employment measures were successful for assistance in finding job, subsidised jobs in the private sector and training programs for some groups of participants.

Evaluation of ALMP for OECD countries also suggested that the influence of these measures was heterogeneous (Heckman et al. 1999). While for some part of the participants the impact was large and positive, for other part it was insignificant or even negative. Also, the institutional set-up of a particular program affects the outcome very much. For example, it is possible that in one country such ALMP as subsidised works is really used for all unemployed to give them an opportunity to gain experience of the real work, and so to increase their human capital. However, in some other country the same policy can be used primarily towards some special category of jobless, e.g., women before retirement. So in the second case ALMP will be utilised not to increase human capital, but rather to provide some additional income to unemployed. Moreover, usually for OECD countries the benefits of conducting ALMP were not sufficiently large in reducing unemployment and poverty compared with their costs.

In transition economies the situation with ALMP differed from OECD counties. According to Lehmann (1995), a tremendous jump in unemployment in CEE countries occurred after the start of reforming process. So, governments of these countries tried to implement employment measures to fight with the unemployment. However, most of the scarce financial resources were spent on Passive (like payment of unemployment benefits), not Active Labour Market Policies. In addition, the study suggests that in transition countries real economic growth, general macroeconomic and structural reforms are more powerful in diminishing unemployment than either Passive or Active Labour Market Policies. Consequently, ALMP cannot substitute these strongly needed reforms, but they can generate at least some marginal effect on the decrease of the unemployment in these countries.

Methods used to conduct evaluation of the ALMP are diverse and well developed (Heckman et al. 1999). The practical choice of the method usually depends on the purpose of evaluation and the assumed model of the economy. In addition, as stated above, the ALMP often has heterogeneous outcomes, so these programs affect a range of parameters. For instance, the same program can be efficient for first type of participants in one group of parameters, but inefficient in the other group, and vice versa for second type of individuals. Consequently, the construction of the counterfactuals to judge the ALMP is very sensitive to the choice of the assumptions about the effects of policies under study. Also, different estimators could generate distinct estimates of the impact of programs because of their different assumptions. So, once again the choice of the assumptions about method to evaluate ALMP must be very careful. Furthermore, it is very important to have data of good quality to construct control and treatment groups, and to receive reliable estimates. Lastly, the non-parametric methods for performing evaluations are more preferable to use because they allow a researcher to avoid biases coming from selection of functional forms.

Among different studies of ALMP in transition economies, studies for CEE countries are most relevant for the case of Ukraine because these countries also had planned economy before 1990, they started transition at the same time as Ukraine, and they are quite similar to Ukraine in geographical location and labour force characteristics. Such studies exist for Poland (Kluve et al, 1999), Slovenia (Vodopivec, 1999), Slovakia (van Ours, 2000; Lubyova and van Ours 1999). All these researches use micro level data from either the unemployment registers of labour offices or labour force survey. In this research one can find a description of typical difficulties of conducting evaluation of ALMP in transition countries. They are as follows: rules for the assignment and monitoring of these policies were not established well and clearly, also these rules were weakly enforced, in addition, there was no stable economic environment, and finally available data were of poor quality.

For Poland training and retraining measure was effective in reducing unemployment, while for the cases of intervention works and public works Kluve et al (1999) found that probability of finding a job after the participation in these programs was decreasing for men. In addition, intervention works had no effect for women. For the case of Slovenia Vodopivec (1999) discovered positive short run influence of public works on flowing from unemployment, however, this effect became negative in the long run. Next, a paper on the ALMP in Slovak Republic (van Ours, 2000) detected a positive impact of public works on transition from unemployment to employment and negative impact of the subsidised works. In addition, other analysis of Slovak republic (Lubyova and van Ours 1999) found that training and subsidised jobs in public sector had positive effect on the transition from the unemployment to a regular job, while subsidised jobs in private sector had negative effect on the same variable. To conclude, all these studies showed that ALMP could affect unemployed people in different ways and their influence varied across countries.

This result was probably obtained because of different ALMP institutional set-up, different stages of transformation process in these countries, variability of the enforcement of policy rules, and other factors which I described early. However, these studies proved that evaluation of ALMP is possible not only for OECD countries, but also for transition countries.

The papers described above suggested that the possibility of performing evaluation of ALMP also existed for the case of Ukraine. Among different methods of conducting such research, which were used in these studies, the most appropriate seems to be the duration analysis of the unemployment spells and logit analysis supplemented with Heckman two-stage correction for the possible selection biases. Data availability and assumptions of these two methods that are quite realistic for Ukrainian economy drive this choice.

The other approach which can be used to evaluate effects of ALMP is matching estimation techniques. The deliberate description of this approach can be found in Heckman et al. (1999) and Schmidt (1999). The applications of matching estimators to analyze effects of ALMP in both transition and developed countries (for example, Kluve et al, 1999; Lechner, 1999) seem to indicate that this approach produces precise estimates and corrects heterogeneity among participants and non-participants in ALMP. However, its utilisation demands large and precise datasets, and it involves rather complicated econometric programming. Because the part of the process of the collection of the raw data used in this study is beyond the control of the author, it is very difficult to construct the database needed to employ matching estimators. Also, limited access to the original data leads to composition of the database with the size not sufficient to apply matching estimators to evaluate ALMP (the description and the discussion of the data used in the study can be found in the empirical section of the study). Therefore, it is probably impossible to use this approach in the current study.

Theoretical exposition of the first method of the evaluation of ALMP which I would like to employ, namely, the analysis of duration data can be found in Lancaster (1990) and Kiefer (1988). This methodology is usually used to analyse the duration of different events and it allows a researcher to identify factors which influences the probability of leaving some state. In particular, the duration analysis is often utilised to investigate determinants which influence the duration of the unemployment spells. A review of utilisation of duration analysis of unemployment in transition countries is included in Stetsenko (2003).

From the sizeable set of literature about duration analysis of unemployment data the most interesting for this study are works which use this analysis to find effect of an ALMP on the transition rate from the unemployment to a regular job. Such works exist for Slovak republic (Lubyova et al, 1999; van Ours 2000), Switzerland (Lalive et al, 2000), the USA (Gritz, 1993).

There are two methodologies to evaluate an ALMP using duration analysis. According to the first, the information about participation in the policy is included as explanatory binary variable into the regression in addition to other variables which represent observable individual characteristics. After that we can estimate the effect of treatment on the probability of finding a job, which is simply the coefficient near the "participation" variable. The second approach takes into account not only participation in the ALMP, but also exact timing of this participation. This is done by inclusion in the regression as explanatory variables two time-varying dummy variables: one for time inside the program and the second for time after the program. It permits to explicitly find impact of enrolment into the ALMP on the transition rate to a job and an effect of the completion of the program on the transition rate.

The second method which is applied in this research is logit analysis with the correction of possible selectivity biases using Heckman two-stage procedure. The outstanding description of the utilisation of this methodology to measure treatment effects and evaluate programs can be found in Greene (2000). And the application of Heckman selection procedure to correct for the heterogeneity in measuring efficiency of ALMP in case of transition country is provided by the Vodopivec (1999).

For the case of Ukraine I found only two researches which explore the efficiency of ALMP. Namely, they are EERC Thesis of Kupets (2000) and EERC Thesis of Dmytrotsa (2003). Both studies use macro level data, while my study will employ micro level registry data. The first research identified that training and public works had positive but small effect on reduction of unemployment. Also, training looked to be more effective than public works. The study of Dmytrotsa (2003) suggested similar conclusions that public works and training programs increased the probability of unemployed people to get a job. Also, it was found that impact of these measures was increasing over time.

Chapter 3

THEORETICAL BACKGROUND

In my research I apply the duration data analysis method to study impact of an ALMP on unemployed individuals. This method is used to study transition of the individuals among some states. As the dependent variable this method utilise duration of stay of individuals in some state. The probability distribution of this duration can be described by the following distribution function (Kiefer, 1988):

$$F(t) = Pr(T < t) \quad (5)$$

where T is random variable which corresponds to duration of unemployment spell and t is some value of time.

The survivor function which represents the probability of staying in the unemployment at the some value of t is as follows:

$$Sv(t) = 1 - F(t) = Pr(T \geq t) \quad (6)$$

Next it is possible to express the probability of living unemployment during the interval $[t, t + dt)$ assuming that duration lasts till t as:

$$Pr(t \leq T < t + dt \mid T \geq t) \quad (7)$$

So, now we can define the hazard rate, which is instantaneous rate of leaving unemployment at time t given that unemployment spells last till t, in the following way (Lancaster, 1990):

$$\lambda(t) = \lim_{dt \to 0} \frac{Pr(t \leq T < t + dt \mid T \geq t)}{dt} = \frac{F'(t)}{Sv(t)} = \frac{f(t)}{Sv(t)} \quad (8)$$

where $f(t)$ is density function of t.

Assume that we have data on duration of unemployment of some group of individuals. All unemployment spells are either completed or right-censored. Where right-censoring means that unemployment spells are not completed at the time when we finish observation, but we set time of its ending to the last observed time.

The existing literature (Kiefer, 1988; Lancaster, 1990) proposes several econometric techniques to estimate the impact of different variables on the duration of the unemployment. First, we consider non-parametric models of estimation. The Kaplan-Meier product limit estimator has the following estimators of the survivor function and hazard rate (Kiefer, 1988):

$$\hat{S}v\left(t_j\right) = \prod_{i=1}^{j} \frac{\left(n_i - h_i\right)}{n_i} = \prod_{i=1}^{j} \left(1 - \hat{\lambda}_i\right) \quad (9)$$

$$\hat{\lambda}\left(t_j\right) = h_j / n_j \quad (10)$$

where $\hat{S}v\left(t_j\right)$ stands for estimated survivor function at time t_j, $j \in [1, N]$, N is the sample size, n_j is number of individuals who has duration greater or equal to t_j, h_j is number of spells completed at time t_j. And because of censoring n_j have the following form:

$$n_j = \sum_{i \geq j}^{K} \left(h_i + m_i\right)$$

where m_j is the number of observations censored between t_j and t_{j+1}, K is a number of completed spells.

This nonparametric estimation model is useful for preliminary analysis and it has easy graphical interpretation of estimated survivor functions for different groups of individuals. However, this method does not pay attention to heterogeneity among individuals. So, more complicated models are needed to get more accurate estimates.

The parametric methods of duration data analysis make use of some assumption of the distribution of data. Usually, some family of distributions is considered based on the theoretical results, preliminary plotting of the data or other reasons. On the one hand, this method is good because it allows a researcher to estimate coefficients easily and interpret them in a straightforward way. On the other hand, the parametric models are based on the strong assumptions about distribution of the data which can be very difficult to justify. The other methodology, namely semi-parametric hazard model or piecewise constant hazard model can be seen as approach with less restrictive assumptions about structure of the data. According to this model the hazard is assumed to be constant over some specific interval of time, but it is different for different intervals of survival time. More formally hazard rates can be written in the following way:

$$\ln(\lambda_i(t)) = \ln(\lambda_{01}) + X_i\beta \quad \text{for } t \in [0, \tau_1)$$

$$\ln(\lambda_i(t)) = \ln(\lambda_{02}) + X_i\beta \quad \text{for } t \in [\tau_1, \tau_2)$$

$$\ldots$$

$$\ln(\lambda_i(t)) = \ln(\lambda_{0K}) + X_i\beta \quad \text{for } t \in [\tau_{K-1}, \tau_K)$$

where $\tau_1 \ldots \tau_K$ represent cut points for specific interval of time. There is no consensus in the existing literature about values of these cut points. Some studies propose monthly intervals, other studies – quarters or several quarters. I choose quarterly intervals because they are used more frequently in studies concerning evaluation of the effectiveness of the programs and because the period under study is quite long (more than 1400 days).

So, to perform duration data analysis in this model a researcher needs to construct variables which will vary for different intervals of time, but will be the same within specific interval of time.

The second methodology which I employ in this study is logit analysis with Heckman two-stage procedure to correct for possible selection biases. The idea of application of such procedure to evaluate effectiveness of ALMP and to control for the possible heterogeneity is taken from Vodopivec (1999).

First, to perform the analysis of the influence of the participation in the ALMP on probability of finding a job I construct the variable EX_i which reflects the labour market status of each unemployed individual after some months spending in the search for a job. Particularly, I analyse the impact of the training/retraining program after 1, 2, 3, 4, 5 and 6 months in a search. For the case of public works the effects are estimated after 1, 2, 3, 4, and 5 months. Both in case of training and public works it is impossible to evaluate effect of ALMP for longer time periods because of insufficient number of observations to perform econometric analysis. The variable EX_i can take two values: 0 if after the appropriate number of months an unemployed individual does not find a job, 1 if after the same period this individual finds an occupation.

Second, the effects of participation in ALMP are estimated using logit with the following specification (Greene, 2000):

$$EX_i = \beta' X_i + \delta C_i + \varepsilon_i \quad (11)$$

where X_i is a vector of variables which describe personal characteristics of the unemployed (gender, age, education), β' is estimated coefficients for the variables standing for the corresponding characteristics, C_i is dummy variable which is equal 1 if an individual participated in the ALMP and it is equal 0 otherwise.

After obtaining estimated coefficients using specification given in equation (11) we may analyse possible biases in the estimate of effect of an ALMP. These biases may arise because of self-selection problem. In other words, the unemployed individuals who participated in ALMP may be better motivated, better qualified etc and they may find a job fast even without participation in the program. Also, it might happen that ALMP attracts more individuals with low self-esteem. So, the coefficients in equation (11) and especially effect of ALMP may be estimated with either positive or negative biases. To find out whether there are any biases and to determine the direction and magnitude of them this study uses a Heckman two-stage procedure.

At the first stage I estimated probit equation of participation in ALMP in the following form (Vodopivec, 1999):

$$C_i = \gamma' X_i + \mu' Z_i + u_i \quad (12)$$

where X_i is again a vector of variables which describe personal characteristics of an unemployed individuals and Z_i is a vector of variables that influence the selection into ALMP.

After that the new variable, the inverse Mills ratio, is calculated as follows (Vodopivec, 1999):

$$\lambda_i = \frac{\phi(\gamma' X_i + \mu' Z_i)}{\Phi(\gamma' X_i + \mu' Z_i)} \text{ for the case of participants;}$$

$$\lambda_i = \frac{-\phi(\gamma' X_i + \mu' Z_i)}{(1 - \Phi(\gamma' X_i + \mu' Z_i))} \text{ for the case of non-participants,}$$

where ϕ and Φ are standard normal and cumulative standard normal distributions.

In the second stage I estimated equation (11) adding selection correction variable λ to the equation.

If we assume that u_i and ε_i are joint normally distributed with the correlation ρ, it is possible to rewrite the expectation of exiting unemployment with and without participation in the ALMP in the following form (Greene, 2000):

$$E\left(EX_i \mid C_i = 1\right) = \beta' X_i + \delta + \rho\sigma_\varepsilon \frac{\phi\left(\gamma' X_i + \mu' Z_i\right)}{\Phi\left(\gamma' X_i + \mu' Z_i\right)}$$ for the participants;

$$E\left(EX_i \mid C_i = 0\right) = \beta' X_i + \rho\sigma_\varepsilon \frac{-\phi\left(\gamma' X_i + \mu' Z_i\right)}{\left(1 - \Phi\left(\gamma' X_i + \mu' Z_i\right)\right)}$$ for the non-participants.

The difference in expected value of EX is equal to:

$$E\left(EX_i \mid C_i = 1\right) - E\left(EX_i \mid C_i = 0\right) = \\ = \delta + \rho\sigma_\varepsilon \frac{\phi\left(\gamma' X_i + \mu' Z_i\right)}{\left(1 - \Phi\left(\gamma' X_i + \mu' Z_i\right)\right)\Phi\left(\gamma' X_i + \mu' Z_i\right)} \quad (13)$$

So, we can see that without inclusion of inverse Mills ratio the estimate of would be biased and the bias is represented by the second term in the equation (13).

Chapter 4

EMPIRICAL ANALYSIS

4.1. Data Description

Among different data sources which can be used to perform evaluation of ALMP there are two main types: survey data and administrative data (Heckman, 1999). There are advantages and disadvantages in both types of data. While with survey data it is possible to ask for all needed variables and record them with any precision and within any time interval, this data is often very expensive. On the other hand, administrative data can be very cheap but have little information about basic demographic characteristics or other needed variables. Because for me it is impossible to conduct own survey and because there is no good survey about ALMP in Ukraine, the administrative data is the only source to conduct evaluation of ALMP in Ukraine.

It is possible to argue that usage of Ukrainian registry data on unemployed individuals may introduce possible biases because the distribution of unemployed according to the official definition might be different from the distribution of unemployed according to the ILO definition of unemployed. So, we might obtain biases using our sample and the direction of these biases cannot be determined in advance. However, only registered unemployed individuals can use the ALMP programs in Ukraine. So, because of this feature of ALMP the usage of registry data to evaluate ALMP seems reasonable.

Active Labour Market Policies in Ukraine are state-financed programs which are conducted through Public Employment Centres (PEC). These centres are obliged by Ukrainian legislation to keep records about different aspects of unemployed people. Among other statistics they have records on the participation of an unemployed in different kinds of ALMP. So, registry databases from PECs are the most reliable and accessible source of micro data about ALMP. The existing literature suggests that this data source may be used in evaluation of labour market programs. Examples of usage of such type of data can be found in Angrist (1998), van Ours (2000), Vodopivec (1999).

The database used in this research comes from one of such Public Employment Centres, namely the Public Employment Centre for Dniprovsky district of the Kyiv city. This database consists of 3289 men and women, who registered as unemployed between January 1, 2000 and November 31, 2003. This database includes both individuals who participate in one of the two ALMP described before, and individuals that do not participate in any kind of the program. The first type of individuals is described by the following variables: the labour status history for the period before participation in the program, duration of participation in ALMP, the labour status history for the period after participation in the program, personal characteristics (age, sex and education). The second type of individuals is described by the same variables except for the duration of participation in ALMP, which is substituted by the labour status history for this period.

There are some obvious drawbacks of such dataset. It does not cover the whole country, so results from the analysis cannot be used to evaluate ALMP in Ukraine overall. In addition, Kyiv city has relatively dynamic labour market. So, if some ALMP is successful it is possible to reason that such effect arises due to better labour market in the capital of Ukraine. However, if an ALMP is identified as inefficient it is possible to conclude that this program will be inefficient in regions with less dynamic labour market. This last conclusion may be done because in depressive or weakly developed regions job destruction exceeds job creation or job creation is almost zero, so number of new vacancies is also near zero. Therefore, knowledge, skills and experience which unemployed individuals gain from ALMP might play no role in search for new jobs. Consequently, even perfectly developed ALMP may look inefficient in these regions.

Also, some unemployed individuals can be without job for a long time but do not register as unemployed. It is impossible to identify such individuals from the existing database, so they are treated as employed. This problem can make the labour market history not very precise and therefore it can distort the estimation process. Hence, some biases may appear because of not precise data.

In this database 626 unemployed individuals received training or retraining ALMP between January 1, 2001 and November 1, 2003. There are 486 women and 140 men. The average age of the sample is 37 years.

The sample of participants in public works program consists of 553 unemployed men and women who obtain ALMP from January 1, 2001 to November 31, 2003. There are 416 women and 137 men in the sample. The average age equals to 42 years.

There are 2110 unemployed in the sample who received neither intervention from training nor intervention from public works program. This sample consists of 1284 women and 826 men.

4.2. Empirical results

First of all I apply simple non-parametric techniques of duration analysis to evaluate effects of ALMP. The survival functions obtained from the data using Kaplan-Meier product limit estimator are presented in Figure 1. To calculate the duration time I used the following method: for non-participants in any program the duration time is simply equal to time of exit from unemployment minus enter time. For the case of training program we are interested in the effect of decrease of the length of unemployment after participation in ALMP, so the duration is calculated as exit time minus time of finishing of ALMP. And for public work I use the same procedure to calculate the duration time.

From the Figure 1 it is possible to conclude that survival function for whose having training are lower than for other groups. So, these people find jobs faster and this fact can be interpreted as follows: after the participation in the ALMP the unemployed people flow out of the unemployment faster than the unemployed who do not participate. Also, the similar effect of the public works is ambiguous. While for some duration of unemployment it is negative in sense that survival function is above the survival function for non-participants, for some other it is below. This pattern of survival function may indicate that public works has negative effect in the short run but after 200 days this effect becomes positive.

The results of fitting the semi-parametric approach to analyse duration data using time invariant dummies to represent participation in the ALMP are presented in table 2 and table 3. From these tables we can conclude that after controlling for different factors such as age, education and gender the participation in the training results in higher hazard and therefore faster moving out of unemployment. On the other hand, controlling for the same factors we obtain lower hazard for participants in the public works and therefore they stay longer in the unemployment. Hence, we can conclude that according to this specification training has positive effect in reducing unemployment time while public works has negative effect. Most of the control variables have expected effects or they are insignificant. For example, being a female prolongs duration of unemployment which is consistent with the fact that potential employers seem to value female workers less because of high possibility of maternity leave for them. Also, this result is consistent with findings of other studies (Stetsenko, 2003). Younger people tend to flow out of unemployment faster which is shown by higher hazard ratios near dummies representing individuals of younger age.

Tables 4 and 5 show results of semi-parametric piecewise constant models with time varying dummy variables for the case of public works and training. Particularly, from table 4, which presents results for the public works, it is possible to conclude that for both time spent inside the program and time after the participation in this ALMP there are no significant effects on the probability of exit from the unemployment. As in the case of time invariant variables the significant control variables have coefficients with expected signs.

According to table 5, which shows the results of the evaluation of training using piecewise constant hazard model, it is possible to conclude that after finishing training courses probability of flowing out of unemployment increases significantly and substantially. Inspection of magnitudes of hazard ratios near control variables reveals that the significant variables have theoretically predicted impact.

Tables 6 and 7 present results of logit analysis of influence of ALMP on probability of leaving unemployment without correction of the selectivity biases for the case of training and public works respectively. Training program has positive and significant effects on the probability of exiting unemployment for all time periods. Public works seems to have no significant effect for first two months, but positive and significant effect for the next months.

Estimates of the effects of training and public works with the correction for the selectivity problem are given in tables 8 and 9. Ideally as the selection variables a researcher should use variables which are highly correlated with

ALMP dummy but have little direct effect on the duration of the unemployment. As far as I know in the existing literature there is no agreement about such variables. Some studies use variables which describe motivation as a selection variables but it is possible to argue that these variables increase effort of unemployed in search for a job and so reduces duration of unemployment. So, in this study for the case of training as the variable which determines selection in program I use age of more than 50 years. This choice was made because this variable is relatively highly correlated with training variable and it is correlated with motivation. For case of public works as a selection variable I utilise gender because of the same reasoning.

From table 8 we can conclude that the effect of training without correction is underestimated. Coefficients for different time periods are significant in both statistical and economic sense. Results that are presented in table 9 allow me to figure out that effects of public works are overestimated without correction. After the correction public works has significant and high negative impact on the probability of finding a job. In all specifications estimates of control variables have expected signs or they are insignificant. They are not included in the text for brevity.

Comparing results of evaluation of ALMP from duration data analysis and logit analysis with the Heckman two-stage procedure to correct for the selectivity and assuming that the direction of biases estimated using second methodology is the same in the estimates of the first method, we may infer that both methods support hypothesis that training has positive impact on reducing unemployment while public works has negative impact.

One of possible reasons why the public works program has negative or insignificant impact on the reduction of the unemployment is the design of the program. Large part of the participants of this program stayed in the program for a few days, moreover a lot of them where forced to participate in the program. In addition, the jobs to which participants were sent were not good in increasing human capital (for example, cleaning or harvesting fruits and vegetables) and participants got low wages. So, the major goal of this program, namely increase of the human capital of unemployed through experience gained at public works is probably not achieved in this case. The proposed solution may be in increasing the quantity and the quality of possible jobs which can be attended through public works program. In addition, the minimum time for participation in public works should be increased to at least one month because participation in any program for one or two days will not give much experience no matter how good the program is.

The analysis of this study also may indicate that the efficiency of training program is less than potential because unemployed individuals of near pension age (more than 50 years old) use enrolment in this program to prolong the time of receiving income support from employment centres. So, impact of this ALMP may be increased if the enrolment of unemployed individuals of near pension age will decrease.

Chapter 5

CONCLUSIONS

Evaluation of Active Labour Market Policies is important because of their influence on the duration of unemployment and because these programs may demand substantial financing from public funds but have small effect on reducing unemployment. The studies of ALMP conducted for the transition countries suggest that ALMP can supplement macroeconomic and structural reforms in a country; rules for the assignment and monitoring of these policies were not established well and clearly, also they were weakly enforced; effects of ALMP depended on institutional set-up and stage of transformation process; ALMP could affect unemployed people in different ways and their influence varied across countries.

Results of the application of duration data analysis and logit analysis with the Heckman two-stage procedure to correct for the heterogeneity to test the efficiency of training and retraining program in reducing unemployment in case of Ukraine seem to indicate that this program has positive effect on the speed of transition from unemployment to employment.

Utilisation of similar methods for the case of public works program appear to show that this ALMP has insignificant or in some specifications negative effect on the reduction of the unemployment.

While in case of the training the obtained results may be due to more dynamic and larger labour market in Kyiv city, for the case of public works conclusions may be generalized for the whole country because even in fast-growing Kyiv this ALMP seems to have no positive impact.

The possible reason why the public works program has no estimated positive impact on the reduction of the unemployment is the design of the program. Analysis of this study reveals that large part of participants stayed in the program for a few days and moreover a lot of them where forced to participate in the program. In addition, the jobs to which participants were sent were quite unpopular and with low wages. So, the major goal of this program, namely increase of the human capital of unemployed through experience gained at public works is probably not achieved in this case. The proposed solution may be in increasing the quantity and the quality of possible jobs which can be attended through public works program. In addition, the minimum time for participation in public works should be increased to at least one month because participation in any program for one or two days will not give much experience no matter how good the program is.

The analysis of this study also may indicate that the efficiency of training program is less than potential because unemployed individuals of near pension age (more than 50 years old) use enrolment in this program to prolong the time of receiving income support from employment centres. So, impact of this ALMP may be increased if the enrolment of unemployed individuals of near pension age will decrease.

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Appendix

Figure 1.

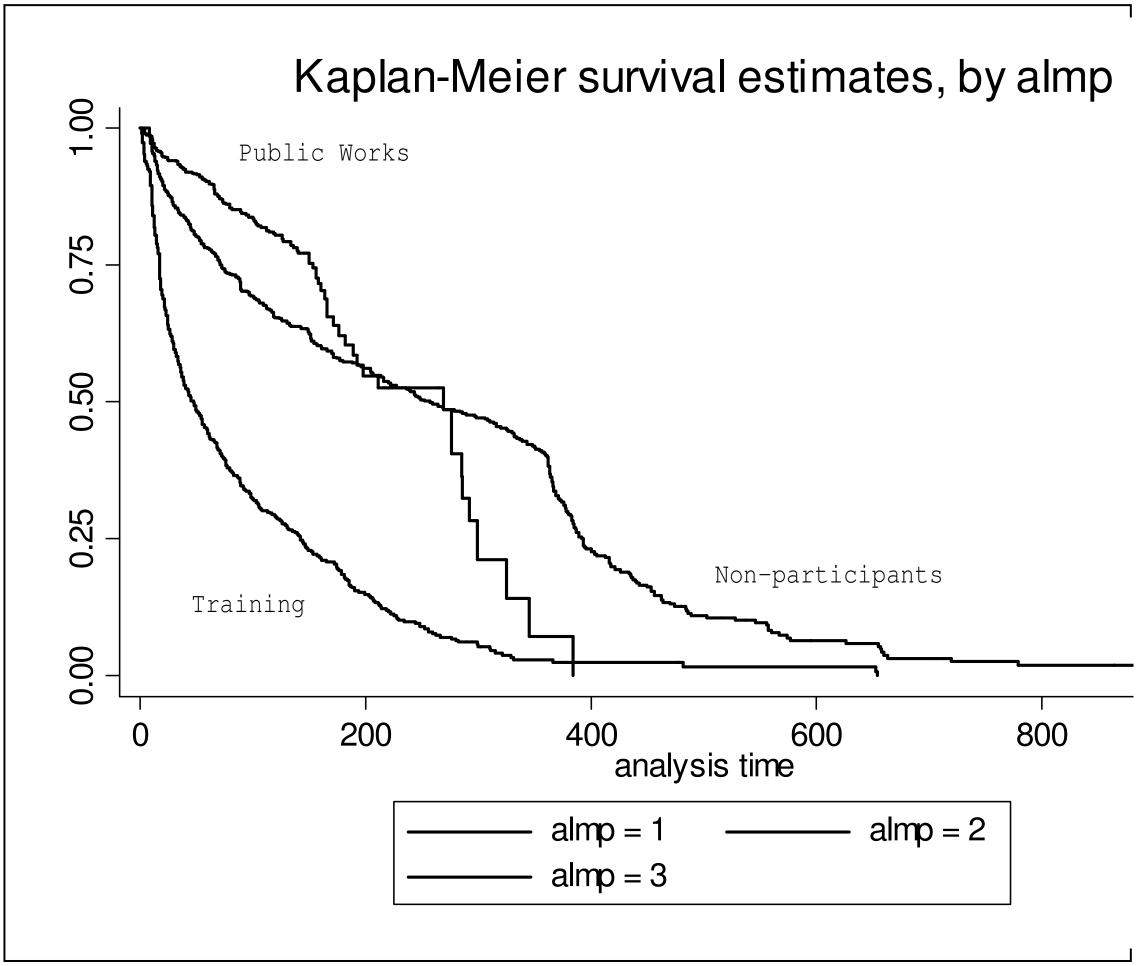

Table 1.
Description of the variables.

Name of a variable	Description of a variable
female	Dummy variable for gender (female=1, otherwise 0).
train	Time invariant dummy variable for participation in training (=1 if a person participated)
pw	Time invariant dummy variable for participation in public works (=1 if a person participated)
age20	Dummy variable =1 if age <20, =0 otherwise.
age25	Dummy variable =1 if 20<=age <25, =0 otherwise.
age30	Dummy variable =1 if 25<=age <30, =0 otherwise.
age35	Dummy variable =1 if 30<=age <35, =0 otherwise.
age40	Dummy variable =1 if 35<=age <40, =0 otherwise.
age45	Dummy variable =1 if 40<=age <45, =0 otherwise.
age50	Dummy variable =1 if 45<=age <50, =0 otherwise.
age55	Dummy variable =1 if 50<=age <55, =0 otherwise.
age60	Dummy variable =1 if 55<=age, =0 otherwise.
hig_edu	Dummy variable=1 if a person has higher education, =0 otherwise.
vocat	Dummy variable=1 if a person has vocational education, =0 otherwise
second	Dummy variable=1 if a person has secondary education, =0 otherwise
bas_sec	Dummy variable=1 if a person has basic education, =0 otherwise.
e1	Dummy variable=1 if 0≤ duration<90, 0 otherwise.
e2	Dummy variable=1 if 90≤ duration<180, 0 otherwise.
e3	Dummy variable=1 if 180≤ duration<270, 0 otherwise.
e4	Dummy variable=1 if 270≤ duration<360, 0 otherwise.
e5	Dummy variable=1 if 360≤ duration<540, 0 otherwise.
e6	Dummy variable=1 if 540≤ duration<630, 0 otherwise.
e7	Dummy variable=1 if 630≤ duration<720, 0 otherwise.
e8	Dummy variable=1 if 720≤ duration<810, 0 otherwise.
e9	Dummy variable=1 if 810≤ duration<900, 0 otherwise.
e10	Dummy variable=1 if 900≤ duration, 0 otherwise.
inside	Dummy variable=1 for the time when an unemployed participated in the ALMP, =0 otherwise.
after	Dummy variable=1 after the time when an unemployed finished ALMP, =0 otherwise.

Table 2.

Duration data analysis with time-constant dummy for training

LR chi2(23) = 582.09
Log likelihood = -1771.5613 Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
female	.5557934	.0438516	-7.44	0.000	.4761615	.6487427
age20	1.809614	.4592543	2.34	0.019	1.100432	2.975835
age25	2.468308	.5085315	4.39	0.000	1.648281	3.696303
age30	1.936964	.3974233	3.22	0.001	1.295607	2.895808
age35	1.409017	.2886141	1.67	0.094	.9431077	2.105091
age45	1.357833	.2735581	1.52	0.129	.9148665	2.015279
age40	1.532083	.3096325	2.11	0.035	1.030992	2.276719
age50	1.154375	.2293088	0.72	0.470	.7820981	1.703854
age55	1.202509	.2400084	0.92	0.356	.8131998	1.778195
hig_edu	.9215654	.079441	-0.95	0.343	.7783066	1.091193
vocat	1.271831	.1389105	2.20	0.028	1.02674	1.575428
second	1.189084	.1143594	1.80	0.072	.984802	1.435742
bas_sec	1.531492	.4029717	1.62	0.105	.9144158	2.564992
e1	.6056183	.058614	-5.18	0.000	.5009756	.7321185
e2	.6929813	.0870799	-2.92	0.004	.5417011	.8865094
e3	.6534959	.1077063	-2.58	0.010	.4730984	.9026807
e4	3.014195	.3832986	8.68	0.000	2.349247	3.867354
e5	1.54879	.3991552	1.70	0.090	.9345886	2.566639
e6	1.572278	.5336401	1.33	0.182	.8084011	3.057961
e7	3.250557	1.172402	3.27	0.001	1.603055	6.591237
e8	1.101085	1.105001	0.10	0.924	.1540251	7.871359
e9	7.74e-06	.0044991	-0.02	0.984	0	.
train	3.438762	.2598208	16.35	0.000	2.965434	3.98764

Table 3.

Duration data analysis with time-constant dummy for public works

LR chi2(23) = 224.65   Log likelihood = -1212.264
Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
female	.7095165	.068315	-3.56	0.000	.5874969	.856879
age20	2.485313	.9140231	2.48	0.013	1.208745	5.110075
age25	3.045672	.7038424	4.82	0.000	1.936306	4.790627
age30	1.957598	.4584354	2.87	0.004	1.237049	3.097848
age35	1.719809	.3975047	2.35	0.019	1.093301	2.705335
age45	1.13891	.2583549	0.57	0.566	.7301291	1.776558
age40	1.520904	.3521346	1.81	0.070	.9661028	2.39431
age50	1.260068	.276266	1.05	0.292	.8199186	1.936499
age55	1.128614	.2420059	0.56	0.573	.7413522	1.718172
hig_edu	.943421	.1047524	-0.52	0.600	.7589142	1.172785
vocat	1.228734	.1629173	1.55	0.120	.94754	1.593377
second	1.124051	.1365111	0.96	0.336	.8859545	1.426136
bas_sec	.7127261	.3633691	-0.66	0.507	.2623944	1.935935
e1	.7692547	.0907	-2.22	0.026	.6105315	.969242
e2	.635565	.1072514	-2.69	0.007	.4565833	.8847079
e3	.8113854	.1435519	-1.18	0.237	.5736287	1.147687
e4	3.7987	.5133798	9.88	0.000	2.914731	4.950758
e5	1.991714	.5390393	2.55	0.011	1.17181	3.385299
e6	2.401232	.8267609	2.54	0.011	1.222812	4.715294
e7	3.319968	1.392124	2.86	0.004	1.459518	7.551937
e8	1.25258	1.258992	0.22	0.823	.1746814	8.981818
e9	.000032	.0097767	-0.03	0.973	4.6e-265	2.2e+255
pw	.6868808	.0748452	-3.45	0.001	.5547933	.8504164

Table 4.

Duration data analysis with time-varying dummy for training

Log likelihood = -1080.5898

LR chi2(24) = 1119.64

Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
after	5.21482	.4131577	20.85	0.000	4.464786	6.090851
inside	8.54e-08	.0000266	-0.05	0.958	2.7e-273	2.7e+258
female	.5075685	.0401785	-8.57	0.000	.4346249	.5927544
age20	1.437701	.363332	1.44	0.151	.8761028	2.359294
age25	2.017487	.4138802	3.42	0.001	1.349553	3.016003
age30	1.497674	.3078644	1.96	0.049	1.00102	2.240741
age35	1.179924	.2424287	0.81	0.421	.7887969	1.764993
age45	1.174899	.2371444	0.80	0.425	.7910287	1.745055
age40	1.070627	.216999	0.34	0.736	.7196367	1.592807
age50	1.029643	.2053781	0.15	0.884	.6964681	1.5222
age55	1.12254	.2247206	0.58	0.564	.7582284	1.661894
hig_edu	.8695965	.07548	-1.61	0.107	.7335579	1.030863
vocat	1.330801	.1456518	2.61	0.009	1.073871	1.649204
second	1.205369	.1174858	1.92	0.055	.9957593	1.459101
bas_sec	1.425058	.3714292	1.36	0.174	.8550159	2.37515
e1	.6889681	.0705281	-3.64	0.000	.5637201	.8420439
e2	.6287646	.0694547	-4.20	0.000	.5063636	.780753
e3	.6544547	.0790825	-3.51	0.000	.5164434	.8293472
e4	1.73326	.195936	4.87	0.000	1.3888	2.163155
e5	.9663566	.1742663	-0.19	0.849	.6786368	1.37606
e6	.9968389	.2296368	-0.01	0.989	.6346553	1.565713
e7	1.650542	.4651551	1.78	0.075	.9500386	2.867556
e8	.9570896	.4868732	-0.09	0.931	.3531383	2.593943
e9	.7392119	.7431894	-0.30	0.764	.1030356	5.303353

Table 5.

Duration data analysis with time-varying dummy for public works

				LR chi2(24) =		290.71
Log likelihood =	-1210.4534			Prob > chi2 =		0.0000

_t	Haz. Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
after	.9297163	.0978842	-0.69	0.489	.756367	1.142795
inside	3.81e-07	.0002354	-0.02	0.981	0	.
female	.6472883	.061818	-4.55	0.000	.5367912	.7805308
age20	2.687167	.991512	2.68	0.007	1.303821	5.538235
age25	3.689307	.8530547	5.65	0.000	2.344914	5.804471
age30	2.106348	.4926356	3.19	0.001	1.331833	3.331273
age35	1.990375	.4589526	2.99	0.003	1.26666	3.127592
age45	1.345947	.3022625	1.32	0.186	.8667059	2.090183
age40	1.520652	.3506355	1.82	0.069	.9677383	2.389472
age50	1.552224	.3402887	2.01	0.045	1.010063	2.385395
age55	1.106859	.2358747	0.48	0.634	.7289517	1.680682
hig_edu	.993521	.1102214	-0.06	0.953	.7993641	1.234837
vocat	1.153118	.1537165	1.07	0.285	.8879826	1.497419
second	1.077889	.1320583	0.61	0.540	.8477904	1.370438
bas_sec	.5127362	.2610362	-1.31	0.189	.1890356	1.390735
e1	.5958621	.077655	-3.97	0.000	.461545	.7692678
e2	.711686	.102011	-2.37	0.018	.5373778	.9425342
e3	.9167776	.1426657	-0.56	0.577	.6757764	1.243727
e4	4.084679	.5110705	11.25	0.000	3.196367	5.219866
e5	2.677376	.5785597	4.56	0.000	1.752958	4.089284
e6	2.92774	.8514899	3.69	0.000	1.655667	5.177164
e7	3.269284	1.27334	3.04	0.002	1.523778	7.014288
e8	1.793191	1.282163	0.82	0.414	.4415734	7.281995
e9	2.424904	2.445144	0.88	0.380	.3360382	17.49849

Table 6.

Estimation of Exit to Employment without Correction for the Selectivity for the case of Training (Marginal Effects)

	Without correction	p-value
After 1 month	0.2750612	0.000
After 2 months	0.3173608	0.000
After 3 months	0.3088118	0.000
After 4 months	0.300252	0.000
After 5 months	0.3157943	0.000
After 6 months	0.2740486	0.000

Table 7.

Estimation of Exit to Employment without Correction for the Selectivity for the case of Public Works (Marginal Effects)

	Without correction	p-value
After 1 month	0.034259	0.436
After 2 months	0.0761012	0.135
After 3 months	0.2055106	0.000
After 4 months	0.2619266	0.000
After 5 months	0.2930152	0.000

Table 8.

Estimation of Exit to Employment with Correction for the Selectivity for the case of Training (Marginal Effects)

	With correction	p-value	Mills ratios	p-value
After 1 month	0.9977627	0.000	-1.87395	0.017
After 2 months	0.9961603	0.027	-1.751152	0.048
After 3 months	0.9450719	0.000	-0.8467306	0.335
After 4 months	0.9597001	0.000	-0.8620563	0.290
After 5 months	0.9901587	0.000	-1.065482	0.146
After 6 months	0.9963251	0.000	-1.065158	0.094

Table 9.

Estimation of Exit to Employment with Correction for the Selectivity for the case of Public Works (Marginal Effects)

	With correction	p-value	Mills ratios	p-value
After 1 month	-0.6896409	0.021	0.9308293	0.120
After 2 months	-0.633628	0.049	0.745562	0.301
After 3 months	-0.9082376	0.000	1.629229	0.058
After 4 months	-0.9544731	0.000	1.898337	0.042
After 5 months	-0.9542267	0.000	1.704666	0.076