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Evidence from Russia

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Abstract

The study estimates the employment effect of vocational training programs for the unemployed in urban Russia. The results of propensity score matching indicate that training programs had a non-negative overall effect on the program participants relative to non-participants.

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JEL classification: J24, J64, J68, C14.

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This study estimates the employment effect of vocational training programs for the unemployed in urban Russia. The results of propensity score matching indicate that training programs had a non-negative overall effect on the program participants relative to non-participants.

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1. Introduction

This note contributes to the scarce literature on the labour policies in transition economies by investigating the employment effect of active labour market programs (ALMP) in the Russian Federation.

Internationally, the usefulness of ALMPs is often a subject of scepticism among politicians as well as employers and jobseekers themselves (e.g., Heckman et al., 1999; Grubb and Martin, 2001; Kluve and Schmidt, 2002). That and tight budget constraints suggest the need for regular monitoring and evaluation of labour market programs (O'Leary et al., 2001). Although evaluation of ALMPs became a common practice in many transition economies of Central and Eastern Europe, until recently there was no rigorous econometric evaluation of ALPMs in Russia (Gimpelson, 2002; World Bank, 2003).

Our paper evaluates the employment effect of government sponsored vocational training programs. Due to unavailability of a countrywide database, we used administrative data from the Public Employment Office (PEO) of Rostov-on-Don, the administrative centre of the Southern Federal District of Russia. The administrative data was combined with a follow-up survey data on sampled unemployed individuals to trace their work history after leaving the PEO.

Using the propensity score matching we compare the employment probabilities of training programs participants with a control group of non-participants. We also controlled for potential heterogeneity in the effectiveness of training programs for blue and white collar occupations.[1]

[1] Professions which were demanded by the local labor market and thus for which training was offered during the period under investigation included accountant, secretary, waitress, bartender, car mechanical, track and bus drivers, as well as some others.

Section 2 presents the methodology and the data. Section 3 presents the results and section 4 concludes the paper.

2. The dataset and sample selection

Registration with the PEO is a pre-requisite for participation in government-sponsored training programs, so our primary data came from the unemployment registry maintained by the PEO of Rostov-on-Don.[2] To collect the data regarding individuals' employment status after leaving the PEO, we implemented a follow-up house-to-house survey. The survey sample consisted of random sample of 2,000 individuals registered with the PEO of Rostov-on-Don in the year 2000. The follow-up survey was conducted in September 2002. The overall survey response rate was 77.3%, about the same for both participants in training programs and non-participants.[3] Our final sample included 1,547 individuals. Among 406 individuals who participate in programs, 152 underwent training for blue-collar professions and 254 underwent training for white-collar professions. This study focused on the employment effects of vocational training programs, and therefore individuals participating in other types of ALMPs (e.g., public works or start-up grants) were not included in the sample.

The outcome of interest was employment probability. The follow-up survey questions were constructed to capture both short-term and long-term effects of the training programs. First, the survey respondents were asked whether they found a job

[2] According to the law "On Employment of the Population in the Russian Federation," an unemployed individual is one who simultaneously satisfies the: (1) belongs to the labor force; (2) is presently without a job and income; (3) is actively searching for a job; (4) is willing to take on a job; (5) has applied to a PEO for assistance in finding a job.
[3] The two main reasons for non-response were refusal to let the interviewer in and refusal to answer the questions. On some occasions it was impossible to locate an individual at the provided address.

after leaving the PEO. Second, they were asked whether they were employed twelve months after leaving the PEO.

According to simple statistics, program participants were generally more likely to find a job upon leaving the PEO relative to non-participants. Among non-participants only 85% found a job comparing to 94% of blue-collar training programs participants and 88% of white-collar programs participants. Twelve months after leaving the PEO, the proportion of employed individuals decreased in all groups. Only 80% of non-participants were employed, comparing to 82% of blue-collar training program participants and 79% of white-collar participants.

3. Empirical strategy and results

To estimate the empirical model we employed the propensity score methodology. Rosenbaum and Rubin (1983, 1984) initiated the literature on matching methods. The authors proposed statistical matching on the basis of predicted probability of participation in the training program, i.e., propensity score. By matching one try to ex-post mimic randomization in control and treatment group in experimental studies. Intuitively, this means that if observations in control and treatment group are similar in all observed characteristics than participation in the training program may explain labour market outcome.

Comparing to other econometric methods matching has two major advantages. First, it provides a convenient test of overlap of observed covariates between treatment and control group. Moreover, if sufficient overlap is achieved treatment effect is estimated non-parametrically.

In recent years matching received a lot of attention in economic literature, e.g. Heckman et al. (1997, 1998), Dehejia and Wahba (1998), Lechner (2002), Smith and Todd (2004). Authors emphasize that validity of matching depends crucially of the absence of unobserved effects. To meet this assumption we selected variables expressing the pre-unemployment work history of individuals and their social-demographic and educational characteristics. We also included variables serving as proxies for individuals' motivation towards employment and period of inflow into the unemployment registry. Table 1 reports mean values for the variables describing individuals in the training and control samples.

To estimate propensity score we followed the algorithm suggested by Dehejia and Wahba (1998, 2002):[4]

1. Start with a logit function with linear covariates to estimate the propensity score.
2. Rank all observations by the estimated propensity score (from lowest to highest).
3. Impose "common support" condition, i.e. discard control group observations with estimated propensity score less than the minimum, or greater than the maximum estimated propensity score for training group observations.
4. Split the sample in 5 blocks of equal score interval and test whether the average propensity scores of training and control observations are the same in every block.

[4] The algorithm for estimation of propensity score and for computation of the average treatment effect on treated (ATT) uses the Stata programs developed by O.Baker and Ichino (2002).

7. Test that the means of each covariate do not differ between the trainees and control in every block.

Following the algorithm we estimate logit function to predict probability of participation in training program and test for balance of covariates. In almost all cases the means were equal at the 5% confidence level, and none of the covariates systematically failed the test in all the blocks. The final distribution of training and control observations is presented in Figures 1 and 2.

To accurately compute the ATT one should precisely match the training and control groups on the basis of propensity score. In practice it is never possible to match the scores precisely, however, and thus four alternative matching methods were used and will be compared: stratification, nearest neighbourhood, radius, and kernel matching. A complete description of the matching estimators used in this paper may be found in O.Baker and Ichino (2002).

The results of the estimation are presented in Table 2. To match treatment and control group we applied four different algorithms. Moreover, radius matching was applied twice with different specification of radius. According to results, individuals who were trained to become blue-collar workers were more likely to find employment comparing to untrained counterparts. Yet, no significant effect was detected in the long run. The long-run effect for the white-collar training is even negative although statistically insignificant. The estimations broadly agree with each other, i.e. positive for blue-collar trainees upon leaving the employment office, but not statistically significant in all other cases.

4. Discussion and conclusions

The main conclusion we can draw from our evaluation results is that the vocational training programs conducted by the Public Employment Office of Rostov-on-Don overall had a non-negative effect on the employment probabilities of program participants relative to non-participants. Participants in blue-collar training had a discernible immediate positive effect, while the participants of white-collar programs did not. These results must be viewed with cautions; the positive effect of blue-collar training may be explained by the larger number of blue-collar vacancies in the labour market of Rostov-on-Don, a big industrial city. For example, in 1999, employment in manufacturing increased by 9.3% while employment in services sector remained static. Moreover, some of the blue-collar training programs can potentially be targeted at the labour demand of a specific firm, although the PEO officers did not indicate to us the existence of any formal agreements to that effect.

Can these results for one particular city be generalized to the rest of Russia? Indeed, there are reasons to believe in the existence of a substantial disparity in the development of different Russian regions. Nevertheless, we believe that the results here can be generalized to a lager group of industrial cities in Russia. According to Russian labour laws, the legislative framework determining eligibility for participation in training programs is uniform. Moreover, large cities in Russia tend to be similar to each other in having a diversified industrial structure and well-developed educational and training infrastructure. Finally, the system of population registration and the under-developed housing market discourage labour mobility, creating stagnant unemployment pools in the cities. Thus labour market processes in large industrial cities tend to be very similar.

From a policy standpoint, the results of our paper are modestly encouraging. The effects of training programs tend be rather limited in both advanced industrial economies and advanced transition economies. Considering the relatively low level of expenditure on ALMPs in Russia and the lack of PEO experience, the effectiveness of some of the training programs is rather surprising. The variation in program effects across different types of training stresses the importance of monitoring the efficient program mix and providing appropriate infrastructure for various types of skill enhancing programs for unemployed individuals.

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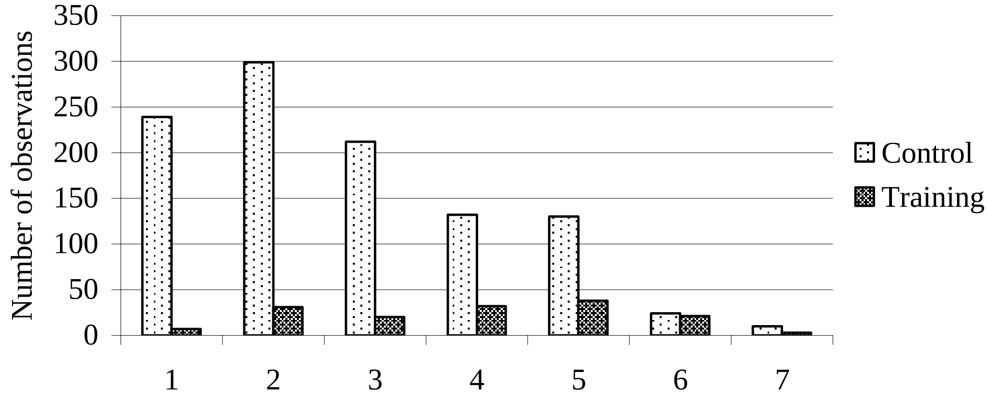
Appendix

Table 1: Mean values for variables in training and control groups.

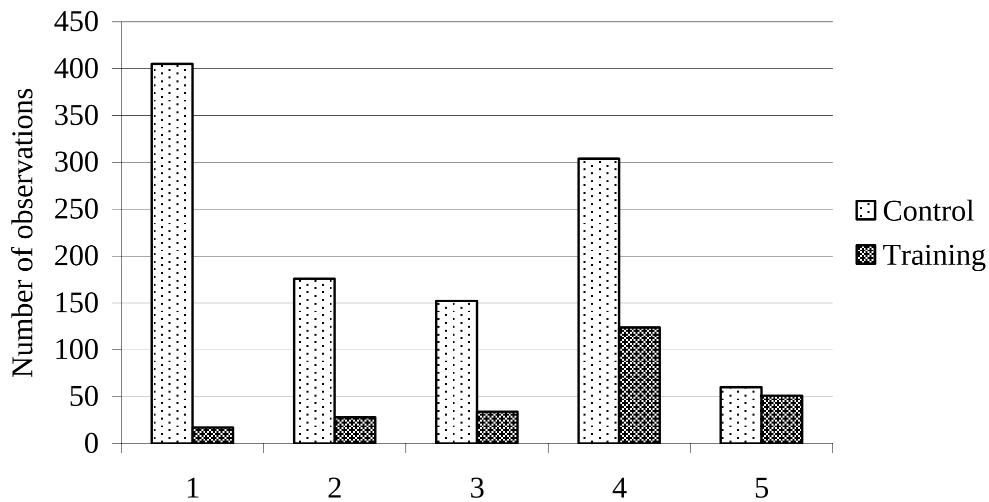
Variable	**Blue-collar training**	**White-collar training**	**Control**
Male	0.428	0.130	0.337
Age $\leq$ 20	0.224	0.165	0.159
Age 21-30	0.408	0.398	0.296
Age 31-40	0.171	0.291	0.180
Age 41-50	0.151	0.126	0.254
Age >51	0.046	0.019	0.111
Married	0.329	0.402	0.449
Number of children	0.454	0.500	0.365
Disabled	0.026	0.031	0.058
Disadvantaged	0.111	0.055	0.056
University education	0.191	0.465	0.340
Technical secondary education	0.177	0.280	0.270
General secondary education	0.336	0.165	0.213
Only primary education or less	0.296	0.091	0.177
No work experience	0.388	0.295	0.249
Work experience 0-5	0.184	0.185	0.155
Work experience 6-15	0.224	0.27	0.203
Work experience >15	0.204	0.244	0.393
Unskilled worker	0.322	0.24	0.189
Blue-collar worker	0.132	0.047	0.102
Skilled blue-collar worker	0.269	0.126	0.220
White-collar worker	0.263	0.465	0.388
Skilled white-collar worker	0.013	0.114	0.102
Pre-unemployment average monthly wage	241.15	475.05	559.15
State ownership	0.407	0.406	0.377
Private ownership	0.184	0.205	0.205
Mixed ownership	0.171	0.197	0.262
No data on ownership	0.237	0.193	0.155
Looking for permanent, full-time job	0.605	0.685	0.691
Winter	0.243	0.146	0.219
Spring	0.263	0.220	0.230
Summer	0.217	0.354	0.266
Fall	0.276	0.279	0.215

Figure 1: Distribution of estimated propensity score, blue-collar training and conrol groups



The region of common support is [0.01277477 - 0.56281613]

Figure 2: Distribution of estimated propensity score, white-collar training and control groups



The region of common support is [0.00720224 - 0.58339802]

Table 2: The effect of training on participant relative to non-participants

Matching method	Effect of blue-collar training: Effect after leaving the PEO	Effect of blue-collar training: Effect 1 year after leaving the PEO	*Number of observations*: *Training*	*Number of observations*: *Control*	Effect of white-collar training: Effect after leaving the PEO	Effect of white-collar training: Effect 1 year after leaving the PEO	*Number of observations*: *Training*	*Number of observations*: *Control*
Stratification	0.094 (3.74)	0.005 (0.14)	152	1046	-0.000 (-0.01)	-0.024 (0.90)	254	1097
Nearest neighbourhood	0.122 (3.02)	0.021 (0.42)	152	165	-0.017 (-0.58)	-0.019 (-0.46)	254	237
Radius (r=0.0001)	0.095 (1.317)	-0.046 (-0.48)	71	125	0.017 (0.33)	-0.000 (-0.001)	114	166
Radius (r=0.0005)	0.084 (2.253)	-0.014 (-0.27)	118	358	-0.022 (-0.60)	-0.030 (-0.66)	203	408
Kernel (bw=silverman)	0.096 (3.749)	0.013 (0.40)	152	1046	0.002 (0.07)	-0.025 (-0.85)	254	1097

t-statistics in parentheses. Standard errors were calculated by bootstrap method (200 replications)