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Time distributed difference-in-differences estimates of return to training

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Abstract: This work is devoted to estimating the individual return to worker's professional training. The research is based on the personnel records of Russian metallurgical enterprise (2006–2010). The main factors that distinguish this paper from others are the following: (I) We focused on the internal labour market, concluding that it has common peculiarities of wage setting concerned with training as an open labour market. (II) We show that mobility-friendly training programs give high returns, and not only in transition economies. (III) We suggest controlling for mobility by choosing a corresponding control group. (IV) We use a robust new specification that is reactive to different dynamics of the dependent variable in treated and control groups in difference-in-differences estimates. (V) We compared three different kinds of training and our conclusions could have practical application. The best way to raise personal earnings is on-the-job training. The internal mobility caused by retraining courses has the same impact on workers as if they lacked retraining. The wages of workers trained in the same field grow randomly for a few months before and after training. Nevertheless it is difficult to prove the causal effect of this kind of training on wage growth.

Subjects: Education & Training; Labour Economics; Econometrics

Keywords: earnings function; Mincerian type equation; difference-in-differences; treatment effect; personnel records; panel data; internal labour market; training; retrain courses; return to training

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PUBLIC INTEREST STATEMENT

Whenever an employer invests resources in his employees, it is only natural for him to expect a rise in productivity coming as a result of the training. The main difficulty in evaluating the return on training consists in determining the best way to measure productivity. It is common for labour economists to link an increase in an employee's productivity with an increase in the employee's wage. However, it is very problematic, among other things, to accurately estimate this return to training as wages vary considerably between categories of employees, types of job and in time. We have developed a method allowing to overcome the main difficulties of estimating return to training, and used this method on data gathered from a Russian metallurgical enterprise.

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1. Introduction

Only recently have some economists tried to open the "black box" of considering a firm in the context of the internal labour market. Addressing part of the problem, in the current paper we estimate the linkage between workers' professional training and their wages.

At first glance this relationship is quite obvious. Certain kinds of trainings definitely increase workers' productivity. In such cases, employers could share with employees the value-added after the trainings. It could be realised through worker promotion with corresponding higher wages.

The other idea is that some trainings can lower future costs of the enterprise connected with infringement of technology, failure of equipment and workers' traumata, etc. In such cases employers could raise workers' wages to appreciate their efforts during the trainings.

The potential gain for employers from the worker's wage increase is the reduction of his external mobility. More loyalty to the firm of such employee eliminates future costs arising from the need to invest in specific human capital of a newly hired worker, if the trained employee left the company.

Despite the obviousness of the above arguments, not all types of training lead to an increase in workers' wages. This idea is not unique as it follows from a review of literature (Section 2 of this paper). Nevertheless, some issues of the considered problem are still not fully investigated. In accordance with this, our article gives the following contribution to this line of research.

Developing the idea of Berger, Earle, and Sabirianova Peter (2001), we argue that, at least in Russia, the main mechanism of worker's wage increase is mobility. By putting workers with the same mobilities as those who were trained in a control group, we show that a return to training (measured by wages) is insignificant. An exception is on-the-job training with apprentices because it is almost impossible to get a correct sample in a control group. Nevertheless, the last result is in agreement with the conclusion of Berger et al. (2001) that returns to such kinds of training that give possibilities to be employed in new fields of job are higher than the return to training in a current worker's field.

In contrast to the works in the same field of research based on survey data, we constrained mobilities within the internal labour market using data from a single firm and show that the above-mentioned mechanism works even in this case.

The other merit of the research is that we consider years when transition period of the Russian economy was over (2006–2010), so the higher return to trainings in a new field is not peculiarity of transition economy, as it was supposed, for example, by Berger et al. (2001) for the period of 1994–1996 and 1998.

To avoid the problem of non-parallel trends in difference-in-difference estimator we suggest the novel idea of time distributed difference-in-differences.

The study is comprehensive enough because it combines and compare in one paper estimates of returns to on-the-job training, retrain courses and training in the same field.

2. Literature review

In the review we shall adhere to a chronological sequence of works reflecting a gradual deepening of the analysis as well as progress in empirical economics.

Regarding the estimates, it is necessary to think first of all about what we measure. De Beyer (1990) called the causal relationship between formal training and workers' wages *participation effect, access to jobs,* and *wage effect. Participation effect* is explained by a decreased probability of changing employment status (to lose work), or the choice to work part-time, as well as reduction in the duration of unemployment. The second effect — *access to jobs* — is the increase of mobility as

a result of training. The third effect — the *wage effect* — is the result of employer behaviour. The employer is forced to pay higher wages to keep a worker in a firm, because after training, a worker expects a wage increase, otherwise he can leave for another job with a better wage.

De Beyer (1990) made OLS estimates of Mincerian earnings functions for skilled manual workers of some enterprises in Kenya and Tanzania in 1980. Training was insignificant both in Kenya and in Tanzania. Three hypotheses were formulated after that: (1) training does not raise productivity; (2) productivity rises, but wages do not; (3) wages rise, but it is impossible to control for this effect by the training dummies.

De Beyer herself rejected the first hypothesis. In support of the second one, one can assume that the employer could cover the costs of training, taking the difference between the increased worker's productivity and wage levels.

The third hypothesis may be valid if low-wage workers receive training, after which they receive wages as highly paid workers. Simple OLS estimates do not react to the wage difference in trained and untrained workers in such cases.

Only the *wage effect* was confirmed by De Beyer (1990). Nevertheless she admits that *access to jobs* is present in her estimates in a form of mobility. The *participation effect* was not measured for lack of corresponding data.

Empirical confirmation of the second De Beyer hypothesis was demonstrated by Conti (2005). She utilised the theoretical background and a procedure described by Dearden, Reed, and Van Reenen (2000) when she matched Italian Labour Force Survey 1996–1999 data with the accounting information from the balance sheets provided by the AIDA *(Analisi Informatizzata Delle Aziende)*. Under the constraints of the Cobb–Douglas production function with constant return to scale, Conti (2005) provided empirical conformation that worker's productivity increases after training.

According to Conti's (2005) estimates, elasticity of productivity in Italian firms with respect to the fraction of workers who were trained is nearby 0.4, and the corresponding wages elasticity equals to 0.1. In comparison, for Great Britain of 1983–1996 Dearden et al. (2000) estimated the corresponding values as 2 and 0.6, respectively.

OLS estimates suffer from the endogeneity problem for the reason that workers' unobservable abilities correlate with training (see the discussions in Albert, García-Serrano, & Hernanz, 2010; Barnow, 1986; Bartel, 1995). If more able and prospective employees are involved in training to a higher extent, the coefficient of training in earnings function is overestimated due to the effect of abilities (Bartel, 1995).

The above-mentioned correlation of abilities with the amount of training has been confirmed in a number of empirical studies. For example, Arulampalam, Booth, and Bryan (2004) showed that in Europe[1] more educated workers got through training more often than others. The same is observed in Canada: employers prefer more educated workers (Parent, 2003). According to Bills and Hodson (2007), workers at the higher stairs of the professional ladder are trained more often than the workers from the lower levels.

In the early works endogeneity of training was controlled by a worker's ability included in the set of explanatory variables in the earnings functions (see, for example, Barron, Berger, & Black, 1999). This method is highly controversial due to the lack of adequate tests of abilities.

The other way to solve the endogeneity problem is the instrumental variables (IV) estimates (see, for example, Wooldridge, 2010). Nevertheless, experience of applied research shows that there is a trade-off between exogeneity and relevance conditions for instruments for respondents'

educational level. The other problem is that IV estimates of return to education are often higher[2] than OLS estimates (Card, 2001). The last effect can be extended to the training.[3] These are the reasons why we do not use IV estimates in the current research.

Endogeneity can be partially controlled by the first-differences estimator (Bartel, 1995). All time-invariant effects (both observable and unobservable) will be excluded from the equations in this case. Additionally, Bartel (1995) controlled the effect of promotion by the use of corresponding binary variables and took into account individuals' heterogeneity by the use of the individual fixed effects model (LSDV estimator). In some models correlation of on-the-job training with workers' individual unobservables were controlled by the worker's productivity before training, included in the model as an explanatory variable (Bartel, 1995). As a result, Bartel's (1995) estimates show a positive significant influence of the on-the-job training[4] on workers' wages.

As far as we can tell, Bartel's (1995) work is the first, where the author has solved the problem of heterogeneity in the preferences of the specific human capital by the different firms. This was made by making empirical estimates on data from a single firm.

Goux and Maurin (2000) considered the French population aged 20–64. They made empirical estimates on a sample of the private sector workers who completed the programs of training from 1989–1992. They noticed that observable and unobservable workers' characteristics influence the selection of training programs. Furthermore, the different training programs had a different impact on the earnings of the workers who remained in the firm and those who left it after the training. The other idea was that inside the firm, specific human capital was more valuable — outside — outside, the general worker's knowledge was appreciated. A competitive labour market firm is less inclined to invest in the worker's general human capital, raising his market value (Becker, 1964). It is important to take into account these ideas when interpreting the returns to training.

It is interesting that according to the estimates made by Regnér (2002) for Sweden (in models with firm and individual fixed effects), the returns made on the general trainings are higher than for the specific trainings. These results are consistent with the model of an imperfect labour market when workers' mobility is limited. In such cases, firms could invest in general human capital (Acemoglu & Pischke, 1999; Stevens, 1994).

Controlling for the above-mentioned effects, Goux and Maurin (2000) wrote a system of three equations. They added to the earnings function two binary choice models (for mobility and selection to participate in a training program). They received the following results for France. (1) Firm-provided training had insignificant impact on wages. (2) Wages and firm profit links were insignificant. (3) There was no direct influence of firm-provided training on mobility. (4) Workers with a higher level of unobserved abilities were preferably involved in training programs.

It is necessary to remember that training has two sides: demand and supply. This was noticed, for example, by Harris (1999). He revealed that workers with the higher tenure had a greater probability to be trained.

Pischke (2001) analysed returns to training in Germany (German Socio-economic Panel, 1986–1989). In his research, training undertaken during leisure time had a greater impact on wages than workplace training. It was explained by the shortening of working hours in the last case.

Some authors have developed original methods to estimate return to training. For example, Schøne (2001) predicted the duration of workplace training to get the necessary qualification and used this level of workplace training as the explanatory variable in earnings function. This methodology gave provided positive impact of workplace training on wages.

Budría and Pereira (2007) explored data of the Portuguese Labour Force Survey (1998–2000). They used a simple OLS and a model described by a system of equations. Significant returns varied by the levels of education and experience.

Depending on the control group, difference-in-differences estimates are insignificant sometimes. For example, Leuven and Oosterbeek (2008) placed workers in a control group with the same characteristics as trained workers but suddenly refused the training. The survey was made by phone in the Netherlands in January–February, 2001. Persons of the age of 16–54 employed in the private sector were included in the sample. OLS and median estimates gave insignificant returns to training.

Albert et al. (2010) made first difference individual and workplaces (as mobility control) fixed effects estimates. They derived insignificant return to training. The same result was observed when the control group was narrowed (Leuven & Oosterbeek, 2008).

No doubt that returns on training depend on the kind of training. Berger et al. (2001) confirmed this. Their research was based on the Russia Longitudinal Monitoring Survey–Higher School of Economics (RLMS–HSE), 1994–1996 and 1998.[5] Berger et al. (2001) discovered higher return to retraining for employment in a new field of work in contrast to the training in a worker's current field. Berger et al. (2001) explained this by the peculiarities of a transition economy.

Travkin (2014) estimated individual returns to training on the RLMS–HSE data of 2004–2011. In his research, returns to training depended on a worker's individual abilities related to their place in the wages distribution.

Denisova, Lazareva, and Tsuchlo (2011) discussed policy implementation of professional training studies. They interviewed the heads of about 1000 Russian industrial enterprises. The authors' conclusion is the statement that the Russian state programs of professional training cannot always cope with the demand of enterprises for the general and branch training. In such a situation, the employer is ready to the bear costs of training the worker only if he will not leave the enterprise after the training. The most obvious way to retain a worker in a firm is to increase wages and investment in specific human capital which cannot be rewarded in the external labour market.

3. Methodology

Taking into account that training effect is distributed in time, we modified the difference-in-differences estimator of earnings function in the following form:

$$\begin{aligned}\ln w_i &= x_i'\beta + \sum_{j=T_1}^{T_2} \beta_j^{(1)} m_{ji} + \sum_{k=1}^{N_i} \beta_k^{(2)} m_{ki}^{<T_2} + \beta^{(3)} mob_i \\ &+ \left(\beta^{(4)} + \sum_{j=T_1}^{T_2} \beta_j^{(5)} m_{ji} + \sum_{k=1}^{N_i} \beta_k^{(6)} m_{ki}^{<T_2} + \beta^{(7)} mob_i\right) tr_i + \varepsilon_i \end{aligned}, \quad (1)$$

where i is the respondent identificator, w is the respondent's wage, x is a column vector of explanatory and control variables (accent means transposition), β is a column vector of parameters, $\beta^{(1)-(7)}$ are scalar parameters, tr is a binary that equals 1 for trained workers and zero for the control group. Binary m_j equals 1 in jth month counted from the month of training graduation, otherwise it equals to zero, and it is missing outside the window $[T_1 - 1, T_2]$. Our preliminary non-parametric estimates showed that workers' changes in wages, which are supposed to be connected with training in the considered enterprise, take place between eight months before and 10 months after the training. For this reason we use $T_1 = -8$, and $T_2 = 11$ in the empirical model (1). The ninth month before the training is a base category for the binaries in the sums from T_1 to T_2. The binaries $m_k^{>T_2}$ control for the wage rise after the respondent's kth training if a person has several episodes of it; the binaries are equal to 1 after T_2 months of kth episode of training, and zero otherwise; N_i is the number of episodes.

In the control group we included respondents who were in the same structural subdivision (16 units) on the same step of the career ladder (59 levels) at the same months as a trained worker. This means that such a control group should automatically take into account internal mobility, because when a respondent changes his position, he is matched to the different respondent from the control group. Nevertheless, in the model we used additional control for internal mobility by the variable *mob*. It has stepwise form, increasing by one at each episode of horizontal or vertical mobility. The initial value of mob (when the worker came to our observation window) is equal to zero. The maximum value of mob is the number of episodes of internal mobility of the worker while we observe him. This variable helps us to explain the average effect of mobility in the corresponding groups of employees.

4. Enterprise and trainings characteristics

The analysed enterprise is from a large metallurgical group of plants. It was created during the Second World War at a distance of 50 km from the regional centre. The enterprise has been an open joint-stock company since 1992.

In the current research we used the information on the personnel of the enterprise, collected for the period from January 2006 to December 2010 from the following sources: personal cards of workers from a personnel department, log-books of training and personnel certification, archival data about dismissed workers, accounting reports on workers' wages, lists of workers and the non-production personnel of a department of work and wages. Monthly data were collected for all employees of the company.

While gathering data we also interviewed numerous bosses of various departments of the enterprise and employees of the management company. After that we understood the organisational structure and personnel schedule of the enterprise. Table 1 shows categories of employees of the enterprise.[6]

According to the information from the enterprise executives, employers focused on the development of new technologies and keeping skilled workers, so that training of employees was current at the plant.

As it was mentioned, in the current research we have identified on-the-job training, retrain courses, and training in the same field. The main criteria of the sample splitting was the differences in mobility after the corresponding trainings.

On-the-job trained workers are mainly apprentices. The given category is heterogeneous in contingent and career prospects. For the majority of them apprenticeship was an intermediate stage on professional ladder. In some cases the apprenticeship was not only the period of investments into specific human capital, but also carried out a role of a trial period before permanent appointment.

Table 1. Categories of employees (number and percentage)

Year	2006	2007	2008	2009	2010
Apprentices	32 (3.0%)	22 (2.1%)	15 (1.5%)	8 (0.8%)	18 (1.9%)
Non-skilled workers	239 (22.3%)	235 (22.0%)	228 (22.7%)	220 (22.9%)	204 (21.4%)
Supporting staff	143 (13.3%)	149 (13.9%)	143 (14.2%)	132 (13.7%)	122 (12.8%)
Skilled professionals	60 (5.6%)	63 (5.9%)	58 (5.8%)	50 (5.2%)	54 (5.7%)
Skilled workers	469 (43.7%)	484 (45.2%)	450 (44.8%)	447 (46.4%)	447 (47.0%)
Supervisors	91 (8.5%)	89 (8.3%)	88 (8.8%)	85 (8.8%)	85 (8.9%)
Middle management	20 (1.9%)	18 (1.7%)	18 (1.8%)	17 (1.8%)	18 (1.9%)
Top management	19 (1.8%)	10 (0.9%)	4 (0.4%)	4 (0.4%)	4 (0.4%)
Total	1,073 (100%)	1,070 (100%)	1,004 (100%)	963 (100%)	952 (100%)

Besides that there were many persons at the enterprise who used an apprenticeship as a temporary job. For example, some university and secondary school students were temporarily employed as apprentices during summer vacations and in internships.

Retrain courses provided the following professional learning: technician, mechanic, electrician, hooker, crusher operator, assistant chemist, cleaner, furnace tender, dogger, machine operator, press operator, shearer, electric and gas welder, burner, forging press operator, crane-, auto- and electric loader driver.

Examples of programs of training in the same field are the following: safety training, mobilisation preparation, transport and customs logistics and nursing.

In accordance with the proposed division, on-the-job trained workers are the most mobile employees. In the second place are employees who took retrain courses. These courses allowed the worker to master a new and adjacent job thereby increasing his wage. Additionally, they increased the employer's flexibility in their use of manpower. Training in the same field does not lead to changes in a job or getting a new profession by the worker. Such trainings are often stipulated legislatively. For some categories of workers these trainings are necessities in their jobs.

The majority of trainings in the enterprise were carried out during the working hours. To prevent the lose in the working hours and corresponding wages, in the month when training was completed or in the subsequent 1–2 months employees usually received rather high monthly payments. Only 18 episodes of retraining and five episodes of training in the same field were off-the-job. During these periods employees received average monthly wages.

5. Empirical results

Table 2 presents the estimates of time-distributed effects of trainings via difference-in-differences methodology described by model (1). The natural logarithm of a worker's hourly wage is used as a dependent variable in the regressions presented in the first three columns of Table 2, the same is presented for monthly wage in the last three columns. Separate estimates were made on the samples of on-the-job trained workers, retrained workers, and workers trained in the same field. The corresponding control group was chosen for each sample. In the control group, people were placed from the same production subdivision and position but without training.

Most of the explanatory variables have self-explanatory names. In the models, we control for the specific human capital (*Tenure* is years of intra-firm experience) and for the general human capital (the educational levels are binary variables). The base category for the levels of education is complete secondary education. Symbolic notations of binaries that indicate training/control group and months before/after training (and corresponding month in control group) are the same as in model (1). The ninth month before the month of training is the base period of time-effect interpretation.

Control variables give obvious results that are easy to understand. We mean return to tenure, education, gender segregation and family status. We will not dwell on this. Let's take a closer look at the returns to trainings.

The majority of the on-the-job trained workers are apprentices who recently came to the company. Many of them are temporary workers that came to the factory on a couple of months of the school break or university holidays. They have relatively high external mobility in comparison with the control group workers. On average, they have smaller hourly and monthly wages in contrast to the control group. We can see that from the negative significant estimates of *tr*'s parameters in Table 2.

On-the-job training is the only kind of training among the considered in the paper that has undoubted return as we can see from the significant parameters of interaction terms of monthly

Table 2. Earnings functions

	Hourly wage			Monthly wage		
	On-the-job training	Retraining	Training in the same field	On-the-job raining	Retraining	Training in the same field
Tenure (months)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.003*** (0.000)
Tenure²/100	−0.000*** (0.000)	−0.000*** (0.000)	−0.000*** (0.000)	−0.000*** (0.000)	−0.000*** (0.000)	−0.001*** (0.000)
Incomplete secon-dary education	−0.051*** (0.017)	−0.090*** (0.015)	−0.027 (0.029)	−0.076*** (0.020)	−0.114*** (0.016)	−0.081** (0.033)
Vocational school	−0.013 (0.022)	−0.084*** (0.019)	−0.053 (0.035)	0.006 (0.026)	−0.061*** (0.020)	−0.098** (0.040)
Technical school	0.093*** (0.022)	0.043** (0.019)	0.221*** (0.024)	−0.008 (0.026)	0.047** (0.020)	0.206*** (0.027)
Incomplete higher education	0.130** (0.064)	0.437*** (0.141)	−0.139* (0.075)	−0.024 (0.076)	0.067 (0.145)	−0.074 (0.087)
Higher education	0.135*** (0.029)	0.424*** (0.032)	0.372*** (0.024)	−0.025 (0.034)	0.451*** (0.033)	0.303*** (0.028)
Male	0.537*** (0.015)	0.476*** (0.013)	0.573*** (0.016)	0.611*** (0.018)	0.563*** (0.014)	0.688*** (0.018)
Married	0.065*** (0.016)	0.034** (0.015)	0.074*** (0.019)	0.002 (0.019)	0.025 (0.015)	0.074*** (0.022)
tr	−0.316** (0.141)	0.012 (0.091)	0.048 (0.088)	−0.411** (0.165)	0.095 (0.097)	0.020 (0.100)
m_{-8}	0.115* (0.065)	−0.057 (0.062)	−0.055 (0.061)	0.266*** (0.079)	0.046 (0.065)	0.140** (0.069)
m_{-7}	0.051 (0.065)	−0.090 (0.059)	−0.003 (0.061)	0.130* (0.078)	0.055 (0.062)	0.077 (0.068)
m_{-6}	0.040 (0.065)	−0.007 (0.058)	0.018 (0.059)	0.082 (0.079)	0.039 (0.060)	0.114* (0.066)
m_{-5}	−0.156** (0.067)	−0.014 (0.058)	0.132** (0.058)	−0.130 (0.080)	0.051 (0.061)	0.121* (0.065)
m_{-4}	−0.134** (0.065)	−0.058 (0.056)	0.142** (0.058)	−0.134* (0.078)	−0.049 (0.058)	0.178*** (0.065)
m_{-3}	−0.182*** (0.070)	−0.092* (0.053)	0.038 (0.059)	−0.279*** (0.084)	0.001 (0.056)	0.190*** (0.066)
m_{-2}	−0.105 (0.076)	−0.029 (0.054)	0.005 (0.058)	−0.179** (0.091)	0.035 (0.056)	0.128** (0.065)
m_{-1}	−0.071 (0.079)	0.009 (0.054)	0.072 (0.058)	−0.144 (0.094)	0.117** (0.057)	0.126* (0.065)
m_0	−0.430*** (0.109)	−0.065 (0.053)	0.018 (0.060)	−1.023*** (0.123)	0.090 (0.056)	0.198*** (0.067)
m_1	0.006 (0.057)	−0.055 (0.053)	0.021 (0.060)	0.065 (0.068)	−0.035 (0.055)	0.163** (0.067)
m_2	0.058 (0.058)	−0.055 (0.053)	0.106* (0.059)	0.059 (0.070)	0.005 (0.056)	0.215*** (0.066)
m_3	0.081 (0.059)	0.030 (0.052)	0.165*** (0.059)	0.020 (0.071)	0.130** (0.055)	0.168** (0.066)
m_4	0.069 (0.061)	0.083 (0.053)	0.109* (0.060)	0.007 (0.072)	0.160*** (0.055)	0.095 (0.066)
m_5	0.114** (0.058)	0.139*** (0.053)	0.088 (0.059)	0.015 (0.070)	0.241*** (0.056)	0.237*** (0.067)
m_6	0.105* (0.058)	0.146*** (0.054)	0.120** (0.060)	0.035 (0.069)	0.210*** (0.057)	0.213*** (0.067)
m_7	0.136** (0.056)	0.139** (0.055)	0.144** (0.064)	0.144** (0.068)	0.175*** (0.058)	0.081 (0.071)
m_8	0.122** (0.058)	0.141** (0.055)	0.103 (0.063)	0.142** (0.069)	0.144** (0.058)	0.198*** (0.071)
m_9	0.123** (0.058)	0.225*** (0.055)	−0.015 (0.060)	0.115 (0.070)	0.273*** (0.058)	0.135** (0.068)
m_{10}	0.113* (0.059)	0.170*** (0.056)	0.053 (0.065)	0.059 (0.070)	0.203*** (0.058)	0.280*** (0.073)
m_{11}	0.219*** (0.060)	0.257*** (0.055)	0.067 (0.066)	0.152** (0.072)	0.307*** (0.058)	0.213*** (0.073)
$m_1 > T_2$	0.172** (0.083)	0.190*** (0.058)	0.246*** (0.040)	0.221** (0.098)	0.152** (0.061)	0.339*** (0.045)
$m_2 > T_2$		0.545*** (0.130)	−0.344*** (0.046)		0.269* (0.138)	−0.386*** (0.052)
$m_3 > T_2$		−0.059 (0.214)	0.895*** (0.116)		0.523** (0.230)	1.007*** (0.133)
$m_4 > T_2$		0.601** (0.279)	0.525*** (0.159)		0.047 (0.302)	0.544*** (0.177)
mob	0.118*** (0.013)	0.065*** (0.009)	0.034*** (0.010)	0.108*** (0.016)	0.034*** (0.009)	0.046*** (0.012)
m_{-8} tr	−0.099 (0.186)	−0.024 (0.124)	0.007 (0.121)	−0.095 (0.221)	−0.262** (0.132)	−0.067 (0.138)
m_{-7} tr	−0.081 (0.180)	−0.036 (0.122)	0.112 (0.121)	−0.064 (0.213)	−0.363*** (0.129)	0.183 (0.137)
m_{-6} tr	−0.043 (0.173)	−0.001 (0.119)	0.019 (0.118)	−0.040 (0.204)	−0.280** (0.127)	0.024 (0.134)
m_{-5} *tr*	0.076 (0.166)	−0.085 (0.116)	−0.022 (0.117)	−0.011 (0.195)	−0.260** (0.123)	0.145 (0.132)

(*Continued*)

Table 2. (*Continued*)

	Hourly wage			Monthly wage		
	On-the-job training	Retraining	Training in the same field	On-the-job raining	Retraining	Training in the same field
m_{-4} tr	0.146 (0.160)	−0.002 (0.112)	−0.016 (0.114)	0.129 (0.188)	−0.142 (0.118)	0.216* (0.130)
m_{-3} *tr*	0.182 (0.158)	0.006 (0.109)	0.030 (0.114)	0.223 (0.185)	−0.116 (0.115)	0.091 (0.130)
m_{-2} *tr*	0.175 (0.159)	−0.036 (0.108)	0.088 (0.113)	0.367** (0.186)	−0.117 (0.114)	0.080 (0.128)
m_{-1} *tr*	0.229 (0.159)	−0.027 (0.107)	0.096 (0.113)	0.442** (0.187)	−0.061 (0.114)	0.219* (0.127)
m_0 *tr*	0.684*** (0.176)	0.029 (0.107)	0.134 (0.113)	1.416*** (0.203)	−0.049 (0.113)	0.135 (0.128)
m_1 *tr*	0.292* (0.150)	0.026 (0.107)	0.108 (0.112)	0.466*** (0.176)	0.039 (0.113)	0.235* (0.128)
m_2 *tr*	0.370** (0.151)	0.062 (0.107)	0.098 (0.112)	0.464*** (0.177)	−0.035 (0.114)	0.162 (0.128)
m_3 *tr*	0.407*** (0.152)	0.018 (0.107)	0.078 (0.113)	0.557*** (0.178)	−0.038 (0.114)	0.300** (0.129)
m_4 *tr*	0.398*** (0.153)	0.122 (0.108)	0.090 (0.115)	0.468*** (0.179)	0.003 (0.115)	0.240* (0.130)
m_5 *tr*	0.430*** (0.152)	0.082 (0.109)	0.001 (0.115)	0.534*** (0.178)	−0.058 (0.116)	0.169 (0.131)
m_6 *tr*	0.554*** (0.152)	−0.000 (0.111)	0.063 (0.117)	0.499*** (0.178)	−0.047 (0.117)	0.228* (0.133)
m_7 *tr*	0.460*** (0.152)	0.096 (0.112)	0.088 (0.125)	0.472*** (0.178)	−0.134 (0.119)	0.239* (0.141)
m_8 *tr*	0.532*** (0.154)	0.124 (0.113)	0.144 (0.124)	0.468*** (0.180)	−0.023 (0.119)	0.182 (0.141)
m_9 *tr*	0.547*** (0.154)	0.019 (0.114)	0.131 (0.124)	0.425** (0.180)	−0.242** (0.120)	0.181 (0.141)
m_{10} *tr*	0.444*** (0.155)	0.131 (0.114)	0.185 (0.131)	0.498*** (0.181)	−0.181 (0.120)	0.160 (0.149)
m_{11} *tr*	0.527*** (0.156)	−0.057 (0.114)	0.133 (0.133)	0.550*** (0.182)	−0.114 (0.120)	0.086 (0.150)
$m_1 > T_2$ *tr*	−0.046 (0.095)	−0.007 (0.078)	−0.132** (0.055)	−0.134 (0.113)	−0.117 (0.083)	−0.169*** (0.063)
$m_2 > T_2$ *tr*			0.378*** (0.073)			0.426*** (0.083)
$m_3 > T_2$ *tr*			−0.338* (0.175)			−0.420** (0.200)
$m_4 > T_2$ *tr*			−0.480** (0.231)			−0.471* (0.261)
mob *tr*	−0.111*** (0.021)	−0.008 (0.020)	−0.008 (0.025)	−0.084*** (0.025)	0.023 (0.021)	0.005 (0.028)
Constant	3.792*** (0.052)	3.939*** (0.047)	3.837*** (0.050)	8.588*** (0.063)	8.638*** (0.050)	8.374*** (0.057)
Observations	7,399	10,398	6,222	7,899	10,972	6,665
Adj. R^2	0.229	0.176	0.297	0.206	0.183	0.307
F-statistics	41.6	40.1	44.8	38.9	44.0	50.2

Note: Standard errors in parentheses.
*Significance level at $p < 0.1$.
**Significance level at $p < 0.05$.
***Significance level at $p < 0.01$.

binaries with *tr* in Table 2. This kind of training is characterised by high internal mobility, which is associated with a rise in wages. After on-the-job training, wages rise by 60% on average.[7] The effect is significant both for hourly and monthly wages with the exception that the last starts to rise before the training is finished.

Retraining and training in the same field have significant impact only on the monthly wages.[8] For this reason, we discuss only the monthly wages below.

One of the interesting results is that at 5–8 months prior the training workers who decided to be retrained had monthly wages 27–43% less than in the control group. We can see that from the negative significant estimates of the corresponding interaction terms m_{-5} to m_{-8} *tr* in Table 2. Managers of the enterprise in our interviews confirmed that these workers tried to be promoted or change production subsidiary via the retrain courses and following mobility to maintain their real wages at the same level adjusted for inflation. Their internal mobility is really high in comparison to the control group.

Trained in the same field, workers are the less mobile among the other trained workers. Their external and internal mobilities are very similar to the mobility of the control group. For this reason it is hardly possible to associate the rise of their earnings with mobility resulting from the training. Estimates for monthly wages presented in Table 2 confirm this. The interaction terms responsible for the difference-in-differences effects are significant randomly at some months before and after the training. This means that training in the same field was not the only reason for an increase in monthly wages. It looks like there is a common cause (for example, worker's abilities) that raises both the wages and probability of being trained.

6. Conclusion

In this paper, individual return to training was analysed in a context of wage growth. One of the features of our research, highlighting it from the others, is that the data is constrained by the limits of the internal labour market. Unique personnel monthly data were gathered from a Russian enterprise specialised in the iron and steel industry.

One of the strengths of this study that set it apart from other ones is its complex character in relation to the considered types of training and earnings functions. We consider returns to on-the-job training, retrain courses, and training in the same field as for hourly and monthly wages.

Our empirical estimates were constructed in accordance with a preposition that the main share in return to training is the return to mobility. Based on this, we chose a difference- in-differences estimator as the main empirical instrument within the scope of the research. Putting the personnel of the firm from the same steps of professional ladder and production subsidiaries (before and after the training) in a control group, we attenuate the effect of mobility.

For the reason that monthly data are subject to strong fluctuations, we developed empirical specifications for the time-distributed treatment effect. As far as we can judge, this is a novelty for such research. As a result, firstly, this gave us the possibility to consider the detailed (monthly) dynamics of wage setting concerned with trainings in a typical Russian firm. Secondly, it fixes the problem of non-parallel trends that arises in the implementation of a standard difference-in-differences estimator.[9]

For the considered enterprise we reserved the following results. The best way to raise personal earnings is on-the-job training. Internal mobility related to retrain courses impacts wages at the same rate as without retraining. Workers trained in the same field were characterised by the growth of their wages in the months around their training, but we failed to reveal a causal effect of this kind of training on wage growth.

The foregoing results are consistent with the findings of Berger et al. (2001) that return to training in a new area of work was higher in transitional Russia than the return to training in a current worker's field. No doubt that this is a reflection of the great impact of mobility in empirical estimates of return to training. The main differences of the current paper from Berger et al. (2001) are that we showed this, firstly, for the period when transition was over, and, secondly, for the internal labour market.

In the cases of retrain courses and training in the same field, external mobilities of trained workers and the control group were the same. This kind of mobility did not influence significantly the results of our analysis.

Unfortunately we could not follow the histories of dismissed apprentices after their on-the- job trainings. Nevertheless, the specialisation of the enterprise and its geographical position allow us to claim that apprentices are unlikely find the same job outside the enterprise after their trainings. Most of them were temporary workers during the summer holidays and manufacturing interns. If we supposed that they went outside the enterprise to find a better job, our estimates of return to on-the-job training would be underestimated. A correct account of this kind of mobility for them would only increase the already significant estimates.

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Notes
1. Belgium was excluded from the sample.
2. In a case of positive correlation of unobservable abilities with schooling.
3. The search of instruments is aggravated with the binary character of the endogenous explanatory variable in the problem of individual return to training.
4. Three types of training in the American firm of 1986–1990 continued 2–5 days were considered: "Core Program" ("for any individual in the company whose job involves supervising at least one other employee"), "Corporate Employee Development" and "Special-purpose".
5. http://www.hse.ru/en/rlms/.
6. If a particular employee changed his state during the year the longest state was accounted in Table 1.
7. Neglecting gratia payments at the end of training which are controlled by m_0 *tr* interaction term.
8. The corresponding interaction terms (in some rows) are significant only in the last two columns in Table 2.
9. See, for example, well known Ashenfelters "dip" (Heckman, Lalonde, & Smith, 1999), and different abilities effect by Travkin (2014).

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