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THE RETURNS TO TRAINING IN RUSSIA: A DIFFERENCE-IN-DIFFERENCES ANALYSIS

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THE RETURNS TO TRAINING IN RUSSIA: A DIFFERENCE-IN-DIFFERENCES ANALYSIS[2]

This paper investigates the wage return to job-related training using a difference-in-differences estimator to control for unmeasured differences in ability and measured differences in past wages as a proxy for ability and motivation. Estimates use data from the Russia Longitudinal Monitoring Survey from 2004 to 2011. As predicted, positive returns to training are identified, and the returns increase absolutely with the level of past wages, consistent with human capital and selection models.

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Introduction

The experience of developed countries – particularly member-states of the OECD – has shown that employers are actively investing in developing the human capital of their employees. According to research conducted by the World Bank, more than half of the companies in developed countries provide their employees with additional training in one form or another. There is reason to believe that the situation is quite different in Russia[3]. Some studies have shown that the level of investment in additional training in Russia is much lower. This difference can be explained by the fact that employers do not see the point in such investment because it is much easier to lure an employee with the required qualifications than to educate their own. Moreover, Russia faces a problem with high employee mobility, meaning that companies are not sure that they will get a return on their investment (Lazareva et al., 2006).

The question arises about whether investments in human capital are profitable in Russia. Does it bring any benefit to the company? Or are such investments justified only when they are strictly necessary? After all, additional training brings benefits not only to the company, but also increases the human capital of employees. The question is whether training leads to higher labour productivity and, therefore, wages? If this practice reveals positive consequences for an employee in the form of higher wages, then we can assume that the company itself has obtained a positive effect in the form of growth in labour productivity.

The purpose of this study is to evaluate whether additional professional training increases an employee's productivity. An increase in productivity is measured by an increase in wages. A positive effect of additional training on wages will at the same time be considered to be a positive impact on the growth of an employee's labour productivity. In such a case, the positive effects for an employer may justify investment in the human capital of employees.

By 'job-related training' we mean a short-term employer-funded formal training program that is aimed at improving the knowledge and skills of an employee that are necessary to carry out his or her duties. Training may be arranged within the employee's profession or within the framework of an additional (related) profession (for example, an engineer acquiring management skills), off-the-job or on-the-job, and in the workplace or in specialised training centres.

Studies on the effects of human capital investment on wages tend to suffer from contamination by differences in unmeasured ability. For example, if high-ability types receive more training than low-ability types, and these differences are not accounted for, then the returns

[3] The Business Environment and Enterprise Performance Surveys (BEEPS), which are jointly conducted by the World Bank and the European Bank for Reconstruction and Development.
http:. www.enterprisesurveys.org/Data/ExploreTopics/workforce

to human capital will be overstated. To correct for this problem, a difference-in-differences estimator is used for the analysis.

The main advantage of this study (against Russian and other foreign studies) is the use of the double difference-in-differences methodology to evaluate the influence of additional vocational training on salary. This methodology is used to minimize the influence of an individual's skills (unobservable characteristics) on the efficiency of additional training. Without considering this influence the results might be quite "noisy".

Incidence of training: a comparative analysis

Russian studies concerning the incidence of job-related training show that many companies declare that they organise additional training. According to a 2004 survey of manufacturing plants, 68.7% of surveyed companies were training their employees. A similar survey that was conducted in 2008 revealed that only 49.8% of companies were engaged in training (Gimpelson et al., 2010). The share of companies that were engaged in training decreased within the period under review, but these results are consistent with estimates made in leading world economies.

Meanwhile, the involvement of employees and the cost of training in Russia are significantly lower than in leading world economies. According to a 2010 survey conducted by the Federal State Statistics Service[4], 15.8% of employees of large- and medium-sized companies underwent training. The results of a survey that was conducted by the Federal State Statistics Service (Rosstat) are higher than the comparable results of studies dedicated to the incidence of training. All else being equal, this difference can be explained by the fact that larger companies are more likely to provide their employees with additional training due to economies of scale. An analysis of all existing companies will reflect significantly lower shares of trained employees.

The results of other studies confirm the figures of the state's statistics: in large and medium-sized companies that traditionally have more opportunities to invest in training their employees, the share of employees who are trained at the employer's expense is 10-15% (Tan et

[4] On the Additional Professional Training of Employees in Companies for 2010, Rosstat. http:.www.gks.ru/wps/wcm/connect/rosstat_main/rosstat/ru/statistics/population/education/. Information on additional professional training in companies has been prepared for 2010 according to the results of the latest federal statistical survey, which is conducted every 3-4 years. The above information is collected in relation to commercial and non-profit organizations (other than small business entities) of all forms of ownership and types of economic activity (except for public administration and defense, social insurance, religious organizations, households, and extra-territorial organizations).

al., 2007), but the respective average rate is 35-40% in OECD member-states, compared to 60% in Switzerland (Bassanini, 2005).

A study conducted by O. Lazareva, I. Denisova and S. Tsukhlo (Lazareva, 2006), similar to the abovementioned Russian papers, concludes that the proportion of staff that is involved in the training process is extremely low compared to other countries. In addition to this, the level of funding for additional training by employees is insignificant. Moreover, a high level of intercompany mobility of staff undermines the employer incentives to invest in additional training. The mentioned findings are extremely important for our study because it is concerned with the benefits from additional professional training. It turns out that employers, by training a small number of employees, agree to additional training only if they expect to receive benefits or when they cannot work without it (to master new equipment, software, and other advanced technologies)[5]. Based on this, we predict that the impact of additional training in Russia should be at least as high as in developed countries or higher.

Empirical analysis of the impact of additional training on productivity and wages

An employer that invests in the human capital of its employees expects to receive a return in the form of increased labour productivity. According to the theory of rational behaviour, an agent (employer) will not invest if he or she does not expect to be compensated for such expenses in the future. This assumption gave rise to practically all theories on additional professional training. However, a number of researchers have examined the empirical evidence of growth in labour productivity after additional training. To carry out empirical testing Barron et al (1999) studied this issue using American data (the Employment Opportunity Pilot Program and the Small Business Administration Survey). Their estimates show that the growth rate of labour productivity is several times higher than the growth rate of wages, and the results of both polls are identical (Barron et al., 1999).

Several studies compared the growth rate of labour productivity with the rate of wage growth. A study that was conducted on data from the UK shows that the impact of additional training on productivity is more than twice its impact on wages (Dearden et al., 2000).

[5] However, required training is beneficial: without required training, it is not possible to make use of new technologies, and this will drop performance, which leads the company to risk falling behind its competitors.

According to data on additional training in Italy, the increase in labour productivity is more than five times the increase in wages. It should be noted that the impact of additional training on wages is not statistically significant in some regressions, but the impact on performance remains significant in all specifications (Counti, 2005). A comparative analysis of data from Sweden and France shows that the productivity of employees who have undergone training increases 3-3.5 times more than does the respective increase in wages (Ballot et al., 2004).

Measuring productivity is fraught with difficulties. In fact, one can measure productivity only by measuring the issue. However, this approach cannot apply to many categories of employees. Therefore, using an alternative approach, researchers compare the change in the wages of two employees who have undergone training, one who changes jobs after training and one who maintains the same job after training. It is assumed that the new employer made no investment in the new employee's previous training and can afford to pay the employee a wage equal to (or slightly less than) his or her labour productivity. Thus, after training, one can measure the difference between an increase in an employee's wages as paid by the new employer and the increase in the wages of a non-mobile employee. The resulting difference will signify a possible return on investment in the human capital of employees.

An OECD study on 11 European countries shows that the wage growth of 'non-mobile' employees is half as much as the wage growth of employees who changed their jobs (OECD, 2004). In Switzerland, the wage growth of mobile employees is 3-4 times more than that of non-mobile ones (Gerfin, 2004). In a study conducted for Great Britain, the wage of employees who changed jobs increased at the rate of 7.5% versus 2.4% for those who stayed in the former workplace (Booth, Bryan, 2002). Based on U.S. data, P. Lengermann (Lengermann, 1999) demonstrates a significant increase in the wages of 'mobile' employees after long-term training (8.3% versus 4%).

Thus, the increase in the wages of mobile employees is substantially higher. However, such comparison may be performed only in the case of general training. After all, training that is aimed at developing specific skills is valued by only the current employer and will not arouse the interest of others. At the same time, the current employer provides a smaller wage increase after specific training than after general training, because other companies will not pay for unnecessary competencies. H. Regner confirms that the increase in wages is higher after general training than after specific training (Regner, 2002).

In many cases, it is impossible to determine the change in labour productivity. Therefore, researchers use the change in wages after additional training (controlling for the change of other observable individual characteristics and characteristics of the workplace) as a proxy for the growth of labour productivity for an employee. Researchers proceed from the basic assumption that an employer raises wages only after an increase in the level of an employee's skills and competencies. This gives rise to the problem of measuring the return from training (Hansson, 2008).

There are many factors that affect the return from training. First, there are factors that are directly related to the training itself, for example, the duration of training or the direction of the training program. Second, there are an employee's individual characteristics: his or her level of education and skills, sex, qualification, and type activities. Third, there are characteristics of the workplace: whether the company is a monopsonist in the labour market, the financial situation of the company, the type of business, etc. We will focus on some of the above factors.

One of these factors is the relationship between additional training and the initial level of education. There exist several points of view on this issue. The first point of view is that the initial professional education mainly provides general skills for a particular professional area or activity; these skills can be useful at work in most companies in the case that a graduate is going to work in the specialty field. Accordingly, all other things being equal, it is worth training an employee with a lower level of education to fill in the gaps and to consequently ensure an employer's rent after training (Battu et al., 2004; Arulampalam et al., 2004).

Another point of view is that training employees with a higher educational level brings more return to an employer than does training less-educated employees. Two explanations of this approach have been put forward by researchers. First, according to the theory of wage compression, better educated individuals have a higher level of skills and labour productivity, which allows an employer to obtain higher rent by lowering wages 'from above' (Evertsson, 2004). Second, the level of education is an indicator of the level of an individual's abilities. Accordingly, by training more capable individuals, the company obtains the highest increase in labour productivity (Bassinini et al., 2005).

It is the interconnection between an individual's ability level and the impact of additional training that becomes the major issue discussed in many papers on the subject. A series of studies confirm that the impact of additional training on productivity and wages is higher for the most capable employees (Brunello, 2001; Dearden et al., 2000; Booth, Bryan, 2002; Loewenstein, Spletzer, 1999, etc.). Some authors also highlight the existence of a selection effect. All things being equal, companies send their most talented employees to training and thereby increase the wage gap between these employees and their less able and less motivated colleagues (Lengermann, 1999).

However, we need to determine whether researchers measure the return from additional training or the return from an employee's abilities. An employee's high levels of abilities can be demonstrated not only during work, but also in the learning process: a capable employee spends less time for training or acquires more knowledge and skills and thereby attains a higher return from the training. At the same time, the abilities of an individual and a number of other factors (family and friendship relationships, motivation, etc.) have a direct impact on both labour productivity (hence, wages) and the probability of participation in training programs. However, the level of ability, motivation, and communication refer to unobservable characteristics. There is no test that can reliably demonstrate the level of ability or determine the true motivation of a person. It turns out that an assessment of the returns from the training will affect an employee's ability. Thus, this hypothesis was subject to the empirical testing that was described in a study based on French data: researchers came to the conclusion that when employers control the procedure for selecting employees to undergo training courses, the estimated impact of such training falls close to zero (Goux, Maurin, 2000).

Econometric problems of assessing the returns from additional training

A number of works using various econometric models are dedicated to empirically assessing the influence of additional training on wages. The most common method used in this analysis is the OLS method, which estimates the Mincer earnings equation with a dummy variable that denotes the undergone training. This approach allows for the control of all the available data about the individual characteristics of employees and job characteristics (Lynch, 1991; Veum, 1995; Parent, 1999; Goux, Maurin, 2000; Lazareva, 2006; Tan et al., 2007, and many others). The evaluation of the growth in hourly earnings was obtained by using the method of ordinary least squares and reveals that such earnings vary in European countries from 3.7 to 21.6%. Moreover, some authors observe that the estimated returns are the highest in countries where the training incidence is the lowest, such as Greece and Portugal (Bassanini et al., 2005). Because the OLS model assumes the same rate of return for individuals who belong to different sub-groups, this model does not allow the effect of unobservable characteristics to be measured.

To solve the problem that concerns the impact of unobserved variables, such as abilities, motivation, and so forth, the literature makes use of fixed-effects regressions (Veum, 1995; Booth, Bryan, 2002; Loewenstein, Spletzer, 1998; Loewenstein, Spletzer, 1999; Lazareva, 2006). It is assumed that these characteristics do not vary greatly over time and that the indicated method removes their impact on the final estimates. This methodology requires panel data for several periods, which may hinder the use of a correction. Another shortcoming of the method that has been mentioned by researchers is that very few characteristics remain unchanged in the long term, and, thus, an attempt to control these characteristics can bias the results. Any estimates that are obtained by means of the abovementioned analysis are traditionally lower than estimates obtained with the OLS model. A detailed analysis of additional professional training in Europe assessed the impact of training on wages with the method of fixed-effects regression. The results vary from close to no impact in France to a 10% increase in wages in Portugal. Researchers highlight that higher returns in Portugal may be because fewer employees are trained there and that employers can choose the employee who will bring the greatest return (Bassanini et al., 2005).

An alternative way to address the influence of unobserved characteristics is the so-called methodology of 'difference-in-differences.' Carrying out assessments that use the abovementioned methodology, researchers divide the respondents into an experimental group (employees who underwent training) and a control group (depending on researcher choice, the control group may include all other respondents or those who shared the most characteristics with the trained staff). The comparison of the two groups before training allows for the net effect of the impact of additional training on wage growth to be determined (Ashenfelter, Card, 1985; Fitzenbergerz, Prey, 2000; Gerfin, 2004).

The use of instrumental variables allows for the elimination of consequences of the non-random selection of employees for the training programs and is a common method used to assess the impact of training on wages (Parent, 1999; Abadie et al., 2002). The main difficulty of this method lies in the choice of an instrumental variable that should not be correlated with random errors of the model but should have a direct impact on the probability of participation in the training program. For example, in the study of L. Rotar, which is dedicated to additional professional training in Slovenia, the author uses a regional dummy variable. In some regions of Slovenia, the share of personnel who participated in training programs is much higher than in other regions (Rotar, 2012).

A number of studies are dedicated to the assessment of the impact of additional training on wages with the use of the quantile regression method (Bauer, Haisken-Denew, 2001; Hartog, Pereira, Cabral, 2001; Arulampalam, Booth, Bryan, 2004). Based on the above works, we can come to the general conclusion that the impact of additional training varies in different groups. Thus, the study of Abadie et al states that the absolute increase in wages in the first quantile is insignificant despite the fact that the relative index of the wages of women in the first quantile group increased by almost a third, but researchers discovered the opposite situation in the upper quantiles (Abadie et al., 2002).

An evaluation that uses all of the above methods requires a strict functional dependence of the variable that denotes the wage level on explanatory variables. Therefore, some studies used the methodology that is based on comparing the observed individuals by the selection of the control group, by a simple (Matching) selection, or with the application of a compliance index (Propensity Score Matching). The study simulates a natural experiment, where the control group comprises individuals who are not participating in the program but are comparable in their observable characteristics (Aakvik, 2001).

Because the methods of selecting the control group do not allow for the tracking of the impact of changes that happen to an individual over time, the combination of various methods remains possible. For example, in a study based on German data, the authors combined the method of compliance index control group selection (Propensity Score Matching) with the 'difference-in-differences' methodology and obtained estimates at the rate of 4.7-5.9%, which is 1.5-2 times lower than estimates based on the OLS model (8.4-10.2%) (Muehler et al, 2007).

Studies of the return from additional training for Russia

The first study dedicated to the impact of additional training and based on Russian data was conducted by M. Berger, J. Earl, and K. Sabiryanova, which originated from the RLMS-HSE database for 1994-1996 and 1998. The analysis shows that having undergone additional training in the last three years reduces the wage rate, but participation in re-training programs increases wages by 35% (Berger, Earl, Sabiryanova, 2001).

The study of O. Lazareva contains an analysis of the RLMS-HSE data for 2000-2003. The author divides the sample into the public and private sectors to try to avoid confusion over various labour markets. The author uses the average wage for the last year as a dependent variable and performs an assessment with the use of the fixed-effects method. Only training that was paid for by the previous employer turns out to be significantly important (in the market sector, its effect varies from 11 to 19%), most likely because the information about training that was used in the study was too fragmented between different types of training. Furthermore, because of the small number of observations, most of the estimates turned out to be insignificant. The author concludes that the impact of training on wages is less significant in concentrated labour markets. However, this may be because an employer appropriates the major part of the rent and thereby compensates for the cost of training (Lazareva, 2006).

In 2005, the Higher School of Economics in collaboration with the World Bank conducted a survey on manufacturing plants. Tan et al. (2007) examine the impact of training programs on the performance of companies and the distribution of wages, depending on the employee's professional activities. All else being equal, the study evaluates the contribution of additional training to be an 18% increase in wages. However, such an analysis should take into account endogeneity: more financially successful companies pay higher wages and are more likely to organise training programs for their employees (Tan et al., 2007).

The above review of the literature demonstrates that many researchers confirm the presence of a positive impact of additional professional training based on empirical analysis. They conclude that the impact on an employee's labour productivity considerably surpasses the impact on wages. Such analysis should take into account a number of factors that have a direct impact on the return value of additional training. The most important factor among these is the level of unmeasured abilities.

Empirical Analysis Methodology

As the first step to assess the impact of additional training on wages, we use the standard Mincer equation, which is estimated by the method of ordinary least squares. The general equation is as follows:

$$Ln(Wage_i) = \sum_j \beta_j x_{ji} + \gamma D_i + \varepsilon_i \qquad (1.1)$$

where $\mathrm{Ln}(\mathrm{Wage}_i)$ is the logarithm of wages of individual *i*; β_j is the coefficient before x_{ji} – the vector of the control variables; D_i is a dummy variable that indicates that an employee received training in the previous period ($D_i = 1$ in case the employee participated in an additional education program in the period *t* – 1); ε_i includes independent and identically distributed residues.

The vector of the control variables includes the socio-demographic characteristics of the workers (age, sex, marital status, level of education, special experience, professional status, type of activity, duration of the working week), regional characteristics (type of locality, regional dummy variable[6]) and a variable that denominates receiving training at any time in the past, except for the previous period (*t* – 1).

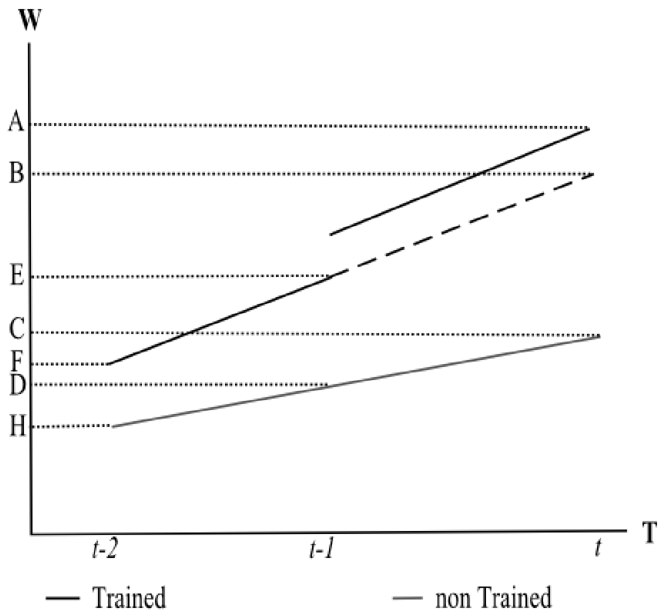
As a tool calculating the net effect of training without the impact of abilities, researchers use the method of 'first difference', or a regression panel data model with fixed effects (Loewenstein, Spletzer, 1999; Booth, Bryan, 2002). This analysis allows the influence of unobserved variables that remain constant over time to be reduced. However, the methodology of fixed effects uses the average estimates for all periods, but the method of 'first difference' makes use of only the previous period. When the method of 'first difference' is used, we obtain more accurate estimates of the abilities based on the assumption that individual abilities remain unchanged from the previous period and that abilities and other unobserved variables can change for the entire period that is covered by the study. Unfortunately, the method of 'first difference' removes from our specification unchanging variables or variables that rarely change over time, such as gender, level of education, or place of residence.

Our goal is to obtain the estimate of variable *A*–*B*, which demonstrates the pay gap. Because point *B* is unknown, we will take into account the dynamics of wage growth that are calculated with the control group of untrained individuals. It should be noted that the first-

[6] Because the data of the RLMS-HSE is not representative of separate regions, we made use of regional dummy variables that indicate their belonging to larger territorial entities - federal districts.

difference methodology can be applied only if the rates of wage growth for trained workers and those who did not undergo training are parallel. However, as has been noted, the share of capable employees among the trained employees is quite high because capable employees are more likely to be trained. Accordingly, the rate of wage growth for employees who are selected for training is, on average, higher than the rate of wage growth for other workers (Figure 1).

Figure 1 – Evaluation of the impact of additional training at various trends of wage growth



We will use the method of ‘double difference-in-differences,’ which allows us to monitor various trends of wage growth for employees. This method was used for estimating returns on training after reforms (Dave et al, 2011). The principal goal of this modification is to control both the previous period ($t - 1$) and the period $t - 2$. The equation for this method will be as follows:

$$\left(\left(A-E\right)-\left(E-F\right)\right)-\left(\left(C-D\right)-\left(D-H\right)\right)=A-B \tag{1.2}$$

If we convert the equation into the format of econometric estimates, we will obtain:

$$\left(Ln\left(Wage_{i,t}\right)-Ln\left(Wage_{i,t-1}\right)\right)-\left(Ln\left(Wage_{i,t-1}\right)-Ln\left(Wage_{i,t-2}\right)\right)=$$

$$=\sum_j \beta_j \left(\left(x_{ji,t}-x_{ji,t-1}\right)-\left(x_{ji,t-1}-x_{ji,t-2}\right)\right)+\gamma\left((D_{i,t}-D_{i,t-1})-(D_{i,t-1}-D_{i,t-2})\right)+ \tag{1.3}$$

$$+\left(\left(\varepsilon_{i,t}-\varepsilon_{i,t-1}\right)-\left(\varepsilon_{i,t-1}-\varepsilon_{i,t-2}\right)\right)$$

This method allows us to neutralise the influence of the rate of wage growth of every individual to better assess the impact of additional training. Based on the empirical findings described in the literature, we predict that additional training provides wage growth. Therefore, the expectation of the wage growth of a trained individual will be calculated as follows:

$$\mathrm{E}\Big(\big(Ln\big(Wage_{i,t}\big)-Ln\big(Wage_{i,t-1}\big)\big)-\big(Ln\big(Wage_{i,t-1}\big)-Ln\big(Wage_{i,t-2}\big)\big)\big|D=1\Big)>0 \tag{1.4}$$

Comparison with the control group allows us to measure the macroeconomic changes that affect the rate of wage growth. If we observe that the rate of wage growth of the control group does not change:

$$\mathrm{E}\Big(\big(Ln\big(Wage_{i,t}\big)-Ln\big(Wage_{i,t-1}\big)\big)-\big(Ln\big(Wage_{i,t-1}\big)-Ln\big(Wage_{i,t-2}\big)\big)\big|D=0\Big)=0 \tag{1.5}$$

then we consider the change in wages of only the experimental group (those who underwent training). However, if the growth rate of wages of the control group changes in one period and this is not due to changes in individual characteristics:

$$\mathrm{E}\Big(\big(Ln\big(Wage_{i,t}\big)-Ln\big(Wage_{i,t-1}\big)\big)-\big(Ln\big(Wage_{i,t-1}\big)-Ln\big(Wage_{i,t-2}\big)\big)\big|D=0\Big)\neq 0 \tag{1.6}$$

then we assume the presence of small fluctuations in the economy as a whole, which affect all groups of individuals.

It should be noted that this method has several limitations. First, we assume that the growth rate of the wages of trained employees is higher than that of untrained individuals who comprise the control group. Second, this method can be used only if the macroeconomic impact (movement, growth, and behaviour) is identical for all groups of workers. In fact, the method can be applied only to periods of economic growth because the wages of individuals with different levels of abilities will vary during a recession or crisis. Thus, in times of crisis, due to the difficult economic situation, the demand for labourers with low skills will decline and they will lose more wages than will more capable employees. Accordingly, assessment of the impact of additional training will be biased due to macroeconomic shocks.

We proceed to verify the hypothesis that the impact of additional training on the wages of capable individuals is higher than is the impact on the wages of individuals with a lower ability level. To verify this hypothesis, we use the quantile regression method[7].

$$Q_{Ln(Wage_i)|X_i}\left(\theta\right)=X_i\beta_\theta, \tag{1.7}$$

[7] A. Abadie, J. Angrist, and G. Imbens used the quantile regression method to divide trained individuals, according to different income levels and evaluated return with the use of the method of instrumental variables (Abadie A., Angrist J., Imbens G., 2002).

In conducting assessment with the use of the quantile regression method, researchers divide the individuals into quantiles based on their wages. All else being equal, this means that all the variables that affect wages are taken into account. In this study, we will use the same vector of control variables as in the OLS model:

$$Ln(Wage_i) = X_i\beta_\theta + \mu_\theta, \qquad \text{if } \theta \in \left[\underline{\theta}\,;\bar{\theta}\right] \;\; \theta \in [\underline{\theta};\bar{\theta}] \tag{1.8}$$

Thus, by using the quantile regression method, we can calculate estimates for each quantile. The total sample is estimated, and individuals from a given quantile are assigned the greatest weight. Because we control various socio-demographic characteristics, a difference in the level of wages can be explained only by a difference in the level of abilities. In other words, the higher the abilities of an individual, the higher the quantile in which he or she will be rated.

It should be noted that the lower the level of the unobserved abilities, the more likely an employee is to receive lower wages. Accordingly, even a small increase in wages in relative terms may be greater than the increase for workers with higher unobserved skills and wages. Therefore, to further evaluate absolute values, we will estimate the regression where the unlogged value of wages will be taken as a dependent variable.

Empirical analysis

Data and descriptive analysis

The study uses the data of the Russia Longitudinal Monitoring Survey of the Higher School of Economics (RLMS-HSE)[8]. The sample was formed by waves of the RLMS HSE for 8 years from 2004 to 2011. The choice of this time period can be explained by the fact that the method of ‘double difference-in-differences’ can only be applied for periods of sustained economic growth, which is exactly the time interval from 2000 to 2008. Retrospective data from respondents include data for 2003. To obtain results comparable with those obtained in previous studies of Russia, the following individuals were excluded from the sample:

- younger than 15 or older than 72 years old;
- unemployed;
- military personnel;
- employees engaged in agriculture.

[8] The Russia Longitudinal Monitoring Survey (RLMS-HSE) was conducted by the National Research University Higher School of Economics and ZAO Demoscope with the Carolina Population Center of the University of North Carolina at Chapel Hill and the Institute of Sociology of the Russian Academy of Sciences. (RLMS-HSE survey sites: *http:. www.cpc.unc.edu/projects/rlms* and *http:. www.hse.ru/rlms*.)

As a result, the sample covered approximately 44,000 observations. The data base contains a question about additional training: *Have you undergone during the past 12 months or are you currently undergoing any professional courses, training courses, or any other courses, including language courses and training in the work place?* The question is formulated to cover as many types of training as possible.

The questionnaire of the RLMS-HSE contains rich information, which includes questions about the source of funding of the additional training[9]. Some training programs were fully or partially paid for by an employer, and others were paid for by employees. We assume that additional training was received only by those employees who participated in employer-paid training programs. We exclude self-financing from our analysis because the question about additional training was worded quite broadly, and the responses could cover types of training that are not directly related to professional activities. However, an employer that sends an employee to training is unlikely to pay for courses that are not directly related to developing professional skills.

Because we do not have information about when the additional training took place (11 months ago or a month before the survey), we cannot be sure that the effect of the training can already be observed. Therefore, to obtain precise estimates, we analyse information about undergoing additional training at least in the previous period (average level is 3.6%). We evaluate the effect of additional training based on changes in wages. So we use a question from the RLMS-HSE questionnaire about the average wages for the year preceding the survey[10]. The information about the average wages for the year allows us to avoid seasonal bias or overstating due to a premium (annual or quarterly). To compare wages received in various periods, we deflate the wages with respect to the base year. We use 2011 as the base year and the annual CPI deflator. The average wage of employees who participated in additional training programs is 17,994.80 rubles, which is 26% more than the average wage of those who were not trained (14,276.20 rubles). Differences across the subsamples of respondents who did or did not receive training, in terms of wages and the control variables, are provided in Appendix Table 1A.

One of the key moments of this study is to single out public sector workers ("civil servants") from among all the respondents in the sample to compare the efficiency of additional vocational training among the sectors. There are currently over 14 million persons in Russia who work in the public sector, which makes up a considerable part of cumulative manpower. Yet the

[9] The question is worded as follows: *'What is the source of funding for your additional training?'*

[10] '*Please specify your average monthly salary paid by the company after taxes for the past 12 months, regardless of whether it is paid on time or not. If you work less than 12 months with the current employee, what was your average monthly salary for the time that you had actually worked in the company? If you receive all the money or a part thereof in foreign currencies, please convert them into rubles and specify the amount of your average monthly salary.*'

public and private sectors have different mechanisms of salary formation and legislative attitudes that affect the corporate policies of the organizations related to personnel training. Thus, the public sector is of interest for our study, as civil servants are obliged to complete additional training at least once every three years. Besides, it should be mentioned that the private sector establishes the salary level by itself, while salary formation in the public sector in practice takes place separately from the private sector, which results in salary gaps between the sectors (Sharunina, 2013). The respondent was referred to the category of public sector workers if: 1) the company he or she works for is 100% state-owned; or, 2) the core activity of the company is healthcare, education, science, culture, or public administration. The share of the public sector workers who took part in the training program in the previous period made 9.5% on an average, which is almost two times more than those trained in the private sector (4.1%). We proceed to the gender distribution of the trained workers. Those workers who underwent training mostly include women (64%), while the share of men who underwent training was 55.7%. Such a high proportion of women can be explained by the fact that employees in the public sector undergo training more frequently, and the share of women working in the public sector exceeds 80%. The average age is almost the same for the groups of trained and untrained employees and is approximately 40 years old.

The following are important differences in the description of the average trained worker and the employee who did not participate in training programs: 1) the level of education; 2) professional status; and, 3) main activity.

Comparing groups of employees by their level of education, it should be noted that, according to researchers dedicated to the issue of additional professional training, employers seek to train the most capable workers (Bassanini et al., 2005). Higher education may be regarded as a signal of the level of abilities of an individual. In fact, workers with higher education count for more than 50% of trained personnel. Moreover, the share of trained workers with a tertiary level of education rises to 78%. The proportion of untrained employees with higher education hardly reaches 25%.

Professional status depends directly on an individual's level of education. Therefore, a high proportion of employees have undergone additional training work as directors or specialists at the highest level of qualification (respectively 7% and 44%), which is two times the figure for employees who did not undergo any additional training. One's professional status can be regarded as indirect evidence of the ability level because a capable individual is more likely to take a position with high-demands to the level of a candidate's qualification. However, employees with various professional statuses undergo training (Table 1A of the Annex).

Assessment of the impact of additional training

The present section contains an assessment of the impact of additional training on wages using the OLS model and the modified method of 'double difference-in-differences'. We control for the following characteristics: gender, age, marital status, presence of children under 18 years of age, level of education, length of service in the current workplace, duration of the work week, professional status, type of activity and size of the company, change in place of work, size of settlement, federal district, and dummy variables that indicate the year when the survey took place. All these characteristics have a direct impact on the level of wages, and so they should be included in the estimated equation to give a more accurate assessment of the impact of additional training on wages.

The specification of the OLS model includes two dummy variables that indicate training (one indicates training received in the previous period, the other indicates training received in any earlier period). The results of the OLS analysis are presented in Table 2A. The results suggest that workers who received training in the previous period on average had a wage of 17.7 percent higher[11].

These results are quite consistent with the previous studies based on Russian data (RLMS HSE). For example, in the work of M. Berger, J. Earle, and K. Sabirianova (2001), re-training increases the salary by over 30%, while in the work of O. Lazareva (2006) the effect of additional training varies from 11 to 19%, depending on the subsample and type of training.

For the 'double difference-in-differences' approach, we used the same vector of control variables as in the estimation with the OLS model. However, as has already been noted in the methodology of the analysis, we use only the period between 2004 and 2008 to assess the dynamics of growth of wages in the economy. The estimate that was obtained in the analysis of the entire sample is 8.3%, which is approximately half of the assessment of the relevant period using the OLS model. This means that there is a correction due to the control of the previous rate of wage growth for an individual and due to control over the difference in growth rates between trained workers and those who have not been trained.

Previous studies show that different groups of workers have different training efficiency (Hansson, 2008). Let us evaluate the efficiency of additional training on different subsamples using our data in the following two ways: 1) separately on the private and public sectors, as the

[11] To estimate the percentage with the use of a logarithmic variable as the dependent variable, we need to substitute coefficient γ of the dummy variable in the formula $(e^{\gamma}-1)*100\%$.

value of additional training differs between sectors, as we described above; and, 2) separately on employees with and without higher education, as higher education can be an indirect indicator of skills.

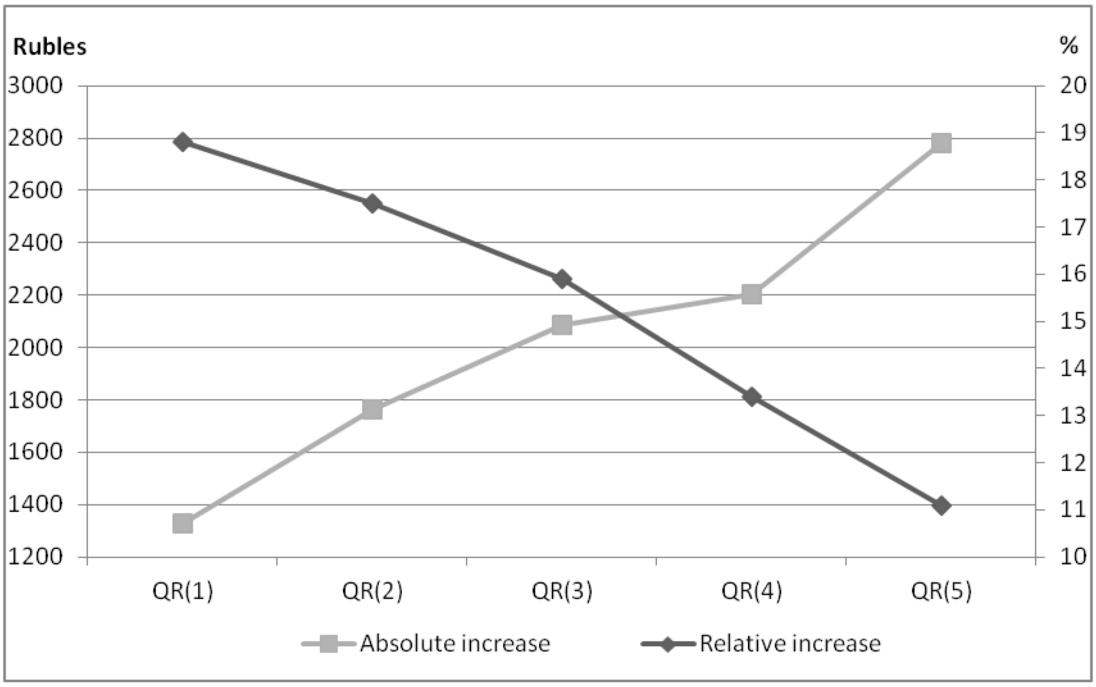
Table 3A shows the results of the influence of additional training on salary in different subgroups using two methods at the same time: OLS and double difference-in-differences. For the purpose of correct comparison, the analysis was based on the sampling for the years 2004-2008 only. The results received using the OLS method show that the efficiency in the public sector equals that in the private sector (15.3% and 14.3%, respectively). The double difference-in-differences demonstrates that the efficiency in the private sector is much higher than that in the public sector (9.8% in the private sector against 5.1% in the public sector). This difference can be explained by a formal approach towards training in the public sector, when a worker completes formal training, which definitely improves his or her skills, but is less effective than training in the private sector. Additional training in the private sector might be more expensive and, therefore, longer in time, more intensive, giving more knowledge and skills, and therewith more cost-consuming than training in the public sector. As we do not touch upon the cost of training in this work, a full comparison of training in the private and public sector is not possible.

A comparison of employees who have different levels of education proves a considerable dissimilarity in efficiency among employees with a higher education (9.1% among employees without a higher education, and 22.2% among those with a higher education). If we assume that employees with a higher education have a higher level of skills than other employees, such a considerable gap between the figures can be explained by differences in skill levels. The double difference-in-differences method, which particularly minimizes the influence of skills on the efficiency of additional training, reflects much less dissimilarity in the efficiency of training among employees with different levels of education (7.2% with higher education against 4.9% of others).

A comparison of the influence of additional training among employees with different levels of education shows that employees with a higher education receive more payoff than employees with lower levels of education. The employer is likely to make a positive decision on investments into the human capital of employees without a higher education only when there is a goal to enhance the efficiency of all employees without exception, rather than of a specific employee: For example, when all employees holding a certain position or who are involved in the same activity are sent for training, such as those who need to work with new technology at a factory. This means that the employer does not independently select the employee who can bring him or her the best improvement in labor efficiency, and therefore the highest return. It is because of the screening problem that we observe a difference in the estimates. In order to answer the question of whether less skillful employees receive a payoff from additional training, let us proceed to the next stage of our analysis.

To evaluate the impact of additional training with the use of the quantile regression method, we will use the same set of control variables as in the OLS model. Thus, we can compare its results with previous estimates. The results of the quantile analysis are presented in figure 3. It can be noted that the first three quantile groups obtain the highest relative return. To compare the wages in absolute values, we estimate a regression with a nominal wage as a dependent variable. The wages of the employees that received training in the first quantile were on average 1,300 rubles higher then the wages of employees who did not. The third and fourth quantiles demonstrate little differences in returns (59% and 73%, respectively, in relation to the first group), but the increase in the fifth quantile is most significant at a rate of approximately 2,800 rubles[12].

Figure 3 – Average values of absolute and relative increase in wages per quantiles after training, RLMS-HSE, 2004-2011



These results are consistent with the results of a study conducted by Abadie et al (2002) based on U.S. data with the use of the quantile analysis method on the basis of the OLS regression, which showed the largest relative increase in the first quantile, and that an increase in

[12] These values are average weighted scores for each period. More detailed results are shown in the working paper of Travkin (2013).

quantiles leads to a decrease in the rate of relative growth. In this respect, we observe the opposite situation in absolute values. Thus, a trained employee from the first quantile receives an extra $367 (increase at a rate of 60.8%) compared to growth of $2,058 (increase at a rate of 8%) in the fifth quantile.

When interpreting the results of quantile regression, we need to take into consideration the absolute values of performance improvement that actually show the highest efficiency among the most skillful employees. As a high relative salary increment among the least skillful ones is associated with the low salary level of these employees (proceeding from the assumption that all else being equal the least skillful employees have less accumulated human capital assets and as a result receive a lower salary). That is why even an insignificant increase in a low salary appears to be extremely significant in relative terms.

The results of the study demonstrate that the increase is not so high for all groups of workers. However, it should be noted that the RLMS-HSE sample includes individuals with a below-average income. Therefore, the rate of wage growth after training throughout Russia may be higher, which may be of particular importance for the cost-benefit analysis of additional professional training.

Conclusion

The main purpose of this paper is to evaluate the rate of return from additional training for Russian workers. The existing estimates for Russia confirm the presence of a return from additional employee training. We conducted an assessment of various groups of workers. The descriptive analysis shows that an employee who has undergone training has a higher level of human capital; on average, such an employee has a higher level of education and occupies a professional position that requires a high level of qualification.

Based on previous studies, we constructed a model and put forward a number of hypotheses. The wages of employees that received training are on average 14.6 percent higher. To obtain more accurate estimates by taking into account the rate of wage growth in the previous period, we use the method of ‘double difference-in-differences’ and estimated the return to be 8.3%. The key issue of this study is whether there are any differences in the return from additional training for individuals with different levels of abilities. To obtain estimates, we divided workers into groups by the level of their abilities that have a direct impact on wages. With the use of the quantile regression method, we found out that individuals with a low level of abilities obtain the highest percentage of increase in wages. This increase occurs because high-skilled individuals receive higher wages on average and the relative increase is more modest, is not so big in size, and corresponds to a smaller proportion of income even though it is bigger in absolute value.

Although employees in the lower quantiles obtain the least absolute return from additional training, it should be noted that this return is positive and statistically significant. The results suggest that the employer does benefit from additional training of employees. After all, an increase in wages means an increase in labour productivity, and there is large empirical evidence suggesting that productivity growth is at least several times higher than the rate of wage growth for an employee based on the analysed literature (Dearden et al., 2000; Ballot et al., 2004). Finally, the employer does benefit from investments in employee training; otherwise, significant positive wage effects would be unlikely.

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Appendix

Table 1A – Descriptive statistics

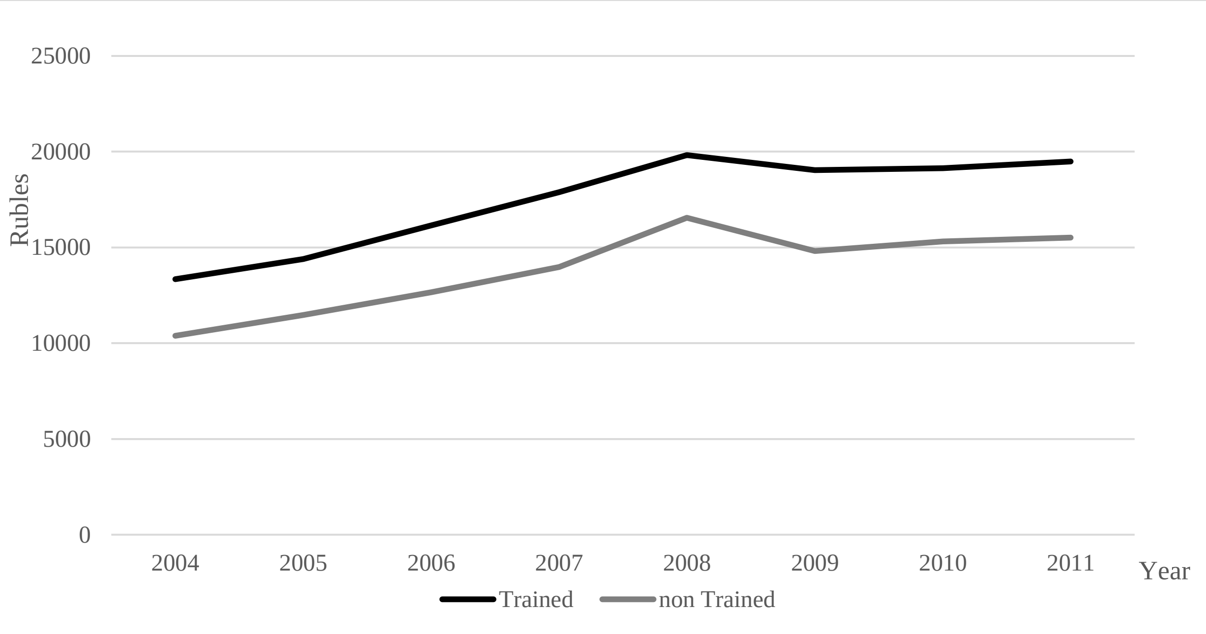
	Mean value		
	Employees trained in the previous period	Non-trained employees	Difference/(s.e.)
Average monthly wages in current prices, rubles	13,943.5	11 160.7	2782.9***/(253.8)
Average monthly wages in 2011 prices, rubles	17,994.8	14 276.2	3718.6***/(298.9)
Marital Status, %			
Married	73.2	71.7	0.017/(0.012)
Presence of children under 18 years of age	53.7	40.1	0.136***/(0.013)
Age, %			
up to 30 years	19.6	26.6	-0.068***/(0.011)
30 - 40 years	31.6	25.4	0.060***/(0.011)
40 - 50 years	26.5	23.5	0.024***/(0.011)
over 50 years	22.3	24.5	-0.025**/(0.011)
Average age, years	40.2	39.6	0.638**/(0.317)
Men, %	36.0	44.7	-0.088***/(0.013)
Level of education, %			
Primary education	0	0.2	-0.002*(0.001)
Lower secondary education	1.8	6.3	-0.044***/(0.006)
Lower initial vocational education	1.1	4.4	-0.033***/(0.005)
Upper secondary education	11.3	21.5	-0.103***/(0.010)
Post-secondary initial vocational education	8.4	14.8	-0.063***/(0.009)
Secondary vocational education	27.0	25.5	0.015/(0.011)
Higher education	50.5	27.2	0.230***/(0.011)
Average length of service in the current company, years	10.1	7.6	2.473***/(0.230)
Professional status, %			
Managers	7.3	4.0	0.032***/0.005)
Specialists with the highest level of qualification	42.7	18.4	0.244***/(0.010)
Specialists with mid-level qualification	21.5	18.3	0.030***/(0.010)
Employees engaged in information preparation	3.8	6.5	-0.027***/(0.006)
Service workers	4.6	10.7	-0.0623***/(0.008)
Skilled workers	8.7	13.3	-0.046***/(0.009)
Operators and others	9.9	16.2	-0.063***/(0.009)
Unskilled workers	1.6	12.6	-0.109***/(0.008)
Type of activities, %			
1. Light and food industry	2.8	6.2	-0.041***/(0.006)
2. Civil engineering	2.0	3.3	-0.016***/(0.005)
3. Military-industrial complex	1.1	2.1	-0.012***/(0.004)
4. Oil and gas industry	6.2	2.5	0.035***/(0.004)
5. Other branches of heavy industry	4.0	3.9	0.001/(0.005)
6. Construction	3.7	8.4	-0.047***/(0.007)
7. Transportation, Communication	7.7	9.3	-0.016**/(0..007)
9. Army, Ministry of Internal Affairs, Security forces	4.5	4.8	-0.003/(0.005)
10. Management bodies	2.8	2.4	0.04/(0.004)

11. Education	24.6	10.1	0.145***/(0.008)
12. Science, Culture	3.2	3.6	-0.004/(0.005)
13. Health	17.1	8.5	0.086***/(0.007)
14. Trade, Domestic services	7.3	17.2	-0.099***/(0.010)
15. Finance	3.3	2.1	0.012***/(0.004)
16. Energy industry	3.3	1.7	0.016***/(0.003)
17. Housing and Community Services	2.7	3.7	-0.010***/(0.005)
18. Other	2.3	2.5	-0.002/(0.004)
Public sector, %	44.2	21.7	0.224***/(0.011)
Share of employees who changed jobs in the last year, %	18.0	20.0	-0.02**/(0.004)
Company size, %			
Microenterprise (up to 15 people)	8.6	15.8	-0.073***/(0.009)
Small enterprise (15 - 100 people)	35.9	26.2	0.097***/(0.011)
Medium enterprise (100 - 250 people)	14.9	12.6	0.024***/(0.008)
Large enterprise (over 250 people)	32.5	29.8	0.021**/(0.011)
Average working week, hour	41.7	43.4	-1.774***/(0.305)
Federal district, %			
Central	27.3	29.5	-0.022***/(0.012)
North-West	16.3	10.8	0.055***/(0.008)
Southern	10.7	12.6	-0.019**/(0.008)
Volga	21.5	22.2	-0.007/(0.011)
Ural	10.0	8.4	0.015**/(0.007)
Siberian	11.6	12.2	-0.005/(0.008)
Far Eastern	2.7	4.4	-0.017***/(0.005)
Type of settlement, %			
Moscow, Saint Petersburg	12.8	12.6	0.005/(0.008)
Regional center	38.0	33.1	0.049***/(0.012)
City	27.8	27.6	0.01/(0.011)
Urban-type settlement, village	21.4	26.7	-0.054***/(0.011)
Number of observations	1599	47896	

* — significant at 10%; ** — significant at 5%; *** — significant at 1%.

Source: author's calculations, RLMS-HSE, 2004-2011

Figure 1A – Wage trend (*in 2011 prices)*



Source: author's calculations, RLMS-HSE, 2004-2011

Table 2A – Assessing the impact of additional training on wages using the OLS model

	Coefficient	**s.e.**
Sex (1=male)	0.283***	0.011
Age in years	0.027***	0.002
Age squared (/100)	–0.037***	0.003
Married (1=married)	0.020**	0.009
Presence of children under 18 years of age	0.021**	0.009
Level of education (*elementary*)		
Lower secondary education	0.107	0.086
Lower initial vocational education	0.155*	0.087
Upper secondary education	0.207**	0.086
Post-secondary initial vocational education	0.183**	0.086
Secondary vocational education	0.258***	0.086
Higher education	0.450***	0.086
Job-related training		
Period $t-1$	0.163***	0.015
Period $t-2, \ldots, t-n$	0.117***	0.017
Work tenure in years	0.006***	0.001
Work tenure squared (/100)	–0.008*	0.004
Duration of working week (log)	0.399***	0.015
Professional status (*service workers*)		
Managers	0.468***	0.025
Specialists with the highest level of qualification	0.325***	0.017
Specialists with mid-level qualification	0.179***	0.015

Employees engaged in information preparation	0.040**	0.019
Skilled workers	0.171***	0.018
Operators and others	0.145***	0.017
Unskilled workers	–0.151***	0.017
Company size (*small enterprise 15 - 100 people*)		
Microenterprise (up to 15 people)	–0.169***	0.015
Medium enterprise (100 - 250 people)	0.047***	0.013
Large enterprise (over 250 people)	0.070***	0.018
No information	–0.028**	0.013
Type of activities (*civil engineering*)		
1. Light and food industry	0.311***	0.022
3. Military-industrial complex	0.191***	0.029
4. Oil and gas industry	0.626***	0.030
5. Other branches of heavy industry	0.393***	0.022
6. Construction	0.473***	0.020
7. Transportation, Communication	0.382***	0.020
9. Management bodies	0.263***	0.023
10. Education	0.393***	0.019
11. Science, Culture	0.474***	0.035
12. Health	0.406***	0.028
13. Army, Ministry of Internal Affairs, Security forces	0.126***	0.024
14. Trade, Domestic services	0.200***	0.029
15. Finance	0.275***	0.028
16. Energy industry	0.211***	0.030
17. Housing and Community Services	0.478***	0.034
18. Other	0.325***	0.026
Public sector	–0.292***	0.021
Changed jobs in the last year	0.029***	0.008
Type of settlement (*city*)		
Moscow, Saint Petersburg	0.446***	0.017
Regional center	0.036***	0.011
Urban-type settlement, village	–0.153***	0.013
Federal district (*Ural*)		
Central	0.085***	0.016
North-West	0.254***	0.019
Southern	–0.088***	0.017
Volga	–0.141***	0.016
Siberian	–0.075***	0.018
Far Eastern	0.062**	0.025
Year (*2004)*		
2005	0.111***	0.010
2006	0.244***	0.010
2007	0.369***	0.010
2008	0.502***	0.010

2009	0.439***	0.011
2010	0.465***	0.010
2011	0.482***	0.010
Constant	6.161***	0.109
Number of observations	44 373	
Adjusted R^2	0.488	

* — significant at 10%; ** — significant at 5%; *** — significant at 1%.

Source: author's calculations, RLMS-HSE, 2004-2011

Table 3A – Comparison of the impact of additional training on wages using the OLS-model and the double difference-in-differences model

Sample	**OLS**			**double diff-in-diff**		
	Coefficient, %	**Coefficient/s.e.**	**Number of observations / Adjusted R2**	**Coefficient, %**	**Coefficient/s.e.**	**Number of observations**
Whole sample	***16.4***	*0.152**** *(0.020)*	*24 338* *0.498*	***8.34***	*0.080**** *-0.03*	***5 053***
Private sector	**14.3**	0.133*** (0.027)	17 911 0.490	**9.75**	0.093*** -0.042	3 469
Public sector	**15.3**	0.148*** (0.028)	6 427 0.445	**5.14**	0.050** -0.038	1 307
Without higher education	**9.1**	0.087*** (0.033)	10 837 0.452	**4.91**	0.048* -0.044	3 418
With higher education	**22.2**	0.200*** (0.024)	13 501 0.478	**7.17**	0.069*** -0.043	1 533

* — significant at 10%; ** — significant at 5%; *** — significant at 1%.

Source: author's calculations, RLMS-HSE, 2004-2008.

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