INTERNATIONAL JOURNAL OF
Training and
Development

International Journal of Training and Development 00:00
ISSN 1360-3736
doi: 10.1111/ijtd.12088

The returns to training in Russia: a difference-in-differences analysis

Pavel Travkin and Anna Sharunina

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 training in one form or another. There is, however, reason to believe that the situation is quite different in Russia. Some studies have shown that the level of investment in 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 employees with the required qualifications than to train their own staff. Moreover, Russia faces a problem with high employee mobility, meaning that companies are not sure that they will get a return on their investment. Given these circumstances, the present study examines whether investments in human capital in Russia are profitable. It 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 panel data from The Russia Longitudinal Monitoring Survey – Higher School of Economics from 2004 to 2011. As predicted, positive returns to training are identified and the returns increase absolutely with the level of past wages.

Introduction[1]

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

❒ Pavel Travkin is research fellow at the National Research University Higher School of Economics, Moscow, Russia. Email: ptravkin@hse.ru. Anna Sharunina is research fellow at the National Research University Higher School of Economics, Moscow, Russia. Email: asharunina@hse.ru

[1] This work is an output of a research project implemented as part of the Basic Research Program at the National Research University Higher School of Economics (HSE). The authors would like to thank Vladimir Gimpelson, Michael Lokshin, Sergey Roshchin for their helpful comments. The authors specially thank Anna Lukyanova for a series of valuable suggestions and comments.

employees. According to research conducted by the World Bank, more than half of the companies in developed countries provide their employees with training in one form or another. There is reason to believe that the situation is quite different in Russia.[2] Some studies have shown that the level of investment in 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,[3] 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, 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 training increases an employee's productivity. An increase in productivity is measured by an increase in wages. A positive effect of 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(related) profession (for example, an engineer acquiring management skills), off-the-job or on-the-job and in the workplace or in specialized 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 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 vocational training on wage. This methodology is used to minimize the influence of an individual's skills on the efficiency of training.

Incidence of training: a comparative analysis

Russian studies concerning the incidence of job-related training show that many companies declare that they organize training. According to the survey of manufacturing plants (2004), 68.7% of companies were training their employees. The 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 survey, but these results are consistent with estimates made in leading world economies.

[2] 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

[3] According to the Federal State Statistics Service, the level of hiring and firing rates in recent years is at the level of 30% of all employees (http://www.gks.ru/wps/wcm/connect/rosstat_main/rosstat/en/main). The high level of mobility of Russian employees is also confirmed by various studies (Gimpelson & Sharunina, 2015; Lehmann & Wadsworth, 2000).

Meanwhile, the involvement of employees and the cost of training in Russia are significantly lower than in leading world economies. According to the survey conducted by the Federal State Statistics Service (2013),[4] 13.8% of employees of large- and medium-sized companies underwent training. The results of this survey 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 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 al*., 2007), but the respective average rate is 35–40% in OECD member-states, compared to 60% in Switzerland (Bassanini *et al*., 2005).

A study by Lazareva *et al*. (2006), concludes that the proportion of staff that is involved in the training process is extremely low compared with other countries. In addition to this, the level of funding for training by employees is insignificant. Moreover, a high level of intercompany mobility of staff undermines employer incentives to invest in training. These findings are extremely important for our study because it is concerned with the benefits from training. It seems that employers, by training a small number of employees, agree to 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 training in Russia should be at least as high as in developed countries or higher.

What factors may limit the incentives of companies to invest in employee training?

First is the fear of opportunistic behaviour. This can be influenced by the high level of mobility among Russian employees, as the employee can change employers after the training. Second is the large number of employees with a higher education. According to the OECD report, in 2011, Russia was in 11th place by the number of people with a higher education and in 1st place by the share of people with a tertiary education (OECD, 2013). Higher education provides general skills in which the companies do not need to invest. Thirdly, most of the production in Russia can be attributed to low-technology manufacturing (Gimpelson *et al*., 2010), which simply does not need a highly skilled workforce and, therefore, there is no need to invest in developing the employees skills.

Empirical analysis of the impact of 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 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 training. However, a number of researchers have examined the empirical evidence of growth in labour productivity after training. To carry out empirical testing Barron *et al.* studied this issue using American data. Their estimates show that the growth rate of labour productivity is several times higher than the growth rate of wages (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 training on productivity is more than twice its impact on wages (Dearden *et al*.,

[4] The Professional Training of Employees in Companies for 2013 (www.gks.ru/wps/wcm/connect/rosstat_main/rosstat/ru/statistics/population/education/).

[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.

2006). According to data on training in Italy, the increase in labour productivity is more than five times the increase in wages. 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*., 2006).

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 productivity. Thus, 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 UK, 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, 2005). Based on U.S. data, Lengermann (1999) demonstrates a significant increase in the wages of 'mobile' employees after long-term training (8.3% vs 4%).

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

There are many factors that affect the return to 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 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; 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 (Arulampalam *et al*., 2010; Battu *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 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 (Bassanini *et al*., 2005).

It is the interconnection between an individual's ability level and the impact of training that becomes the major issue discussed in many papers. A series of studies confirm that the impact of training on productivity and wages is higher for the most capable employees (e.g. Booth & Bryan, 2005; Dearden *et al.*, 2006; Loewenstein & Spletzer, 1999). 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 colleagues (Lengermann, 1999).

However, we need to determine whether researchers measure the return to training or the return to 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 to 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 productivity (hence, wages) and the probability of participation in training programs. However, the level of ability, motivation and communication refer to unobservable characteristics. It turns out that an assessment of the returns to 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 to training

A number of papers using various econometric models are dedicated to empirically assessing the influence of 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 (Goux & Maurin, 2000; Lazareva, 2006; Nordlund *et al.*, 2015; Parent, 1999 and many others). The evaluation of the growth in hourly earnings was obtained by using the OLS method and reveals that such earnings vary in European countries from 3.7% to 21.6%. 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 of unobserved variables, such as abilities, motivation and so forth, the literature makes use of fixed-effects regressions (Booth & Bryan, 2005; Loewenstein & Spletzer, 1998, 1999). It is assumed that these characteristics do not vary greatly over time and that the indicated method removes their impact on the estimates. This methodology requires panel data for several periods, which may hinder the use of a correction. 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 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 (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 training on wage growth to be determined (Fitzenberger & 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 (Abadie *et al.*, 2002; Parent, 1999). 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 by Rotar, which is dedicated to 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 training on wages with the use of the quantile regression method. Researchers come to the general conclusion that the impact of training varies in different groups with different level of abilities (Abadie *et al*., 2002; Andersson *et al*., 2014; Arulampalam *et al*., 2010; Bauer & Haisken-Denew, 2001).

Studies of the return to training for Russia

The first study dedicated to the impact of training and based on Russian data (RLMS-HSE for 1994–1998) was conducted by Berger, Earl and Sabiryanova. The analysis shows that having undergone training in the last 3 years reduces the wage rate, but participation in re-training programs increases wages by 35% (Berger *et al*., 2001).

The study by Lazareva contains an analysis of the RLMS-HSE data for 2000–2003. The author divides the sample into the public and market sectors to avoid confusion over various labour markets. The author uses the fixed-effects method and 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 (Lazareva, 2006).

Tan *et al*. 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 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 organize training programs (Tan *et al*., 2007).

The above review of the literature demonstrates that many researchers confirm the presence of a positive impact of training based on empirical analysis. They conclude that the impact on an employee's 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 totraining. The most important factor among these is the level of unmeasured abilities.

Methodology

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

$$Ln(Wage_i) = \beta_j X_{ji} + \gamma D_i + \varepsilon_{it}$$

where $Ln\,(Wage_i)$ is the logarithm of wages of individual i; 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 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 (age, gender, marital status, children under 18, years level of education, tenure, occupation, type of activity, duration of the working week, change in place of work), regional characteristics (type of settlement, regional dummy variable[6]), dummy variables that

[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.

indicate the year when the survey took place 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 model with fixed-effects (Booth & Bryan, 2005; Loewenstein & Spletzer, 1999). This analysis allows the influence of unobservable 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. Unfortunately, these methods remove from our specification unchanging variables or variables that rarely change over time, such as gender, level of education or region.

In addition to this, it is necessary to consider the basic problems with selection of employees:

1. Selection of employees for training; the employer may choose the most productive employees for whom the training will bring maximum returns. Thus, we may overestimate the returns to training. Also, the selection effect can be divided into two components. Firstly, the selection of the employee with the highest level of abilities makes the training easier and learning faster; correspondingly, there is greater development of skills than there could have been for a less capable individual. The second component is the selection of the most appropriate employee for training. For example, quantitative skills training is much more likely to be beneficial for the employee who did not graduate from high school than for employees with a higher math or engineering background. It can be concluded that the less training the employer provides, the easier it is to select employees for whom the return to training is maximized. The same principle should hold at the national level. Russia is among such countries, as the proportion of trained employees here varies from 3% to 15% (Tan *et al.*, 2007);
2. Self-selection; an employee can agree only to training that may increase his or her productivity and wage. As a consequence, the ATT-effect is significantly higher than the ATE-effect. Other things being equal, the more individual the approach the employer takes in offering training programs, the more likely the employee is to agree, and the greater the effect of the training.

Our goal is to obtain the estimate of *A*–*B* (Figure 1), 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-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, 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.

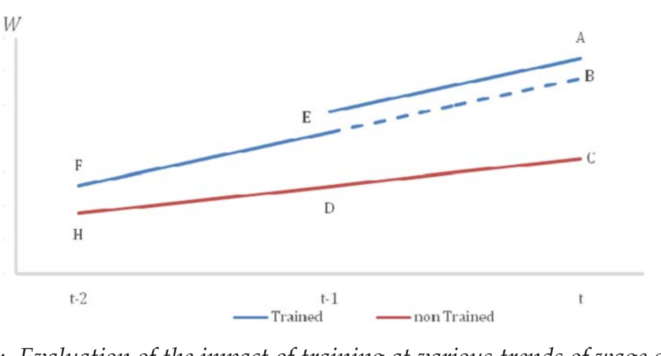

Figure 1: Evaluation of the impact of training at various trends of wage growth.

We will use the method of double difference-in-differences, which allows us to monitor various trends of wage growth for employees. This method is classic difference-in-differences method with pre-treatment period. This method was used for estimating influence on job contract after training (Tattara & Valentin, 2005). 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 (see Figure 1):

$$((A-E)-(E-F))-((C-D)-(D-H))=A-B$$

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

$$\begin{aligned}&\left(Ln\left(Wage_{i,t}\right)-Ln\left(Wage_{i,t-1}\right)\right)-\left(Ln\left(Wage_{i,t-1}\right)-Ln\left(Wage_{i,t-2}\right)\right)\\&=\sum_j \beta_j\left(\left(x_{ji,t}-x_{ji,t-1}\right)-\left(x_{ji,t-1}-x_{ji,t-2}\right)\right)+\gamma\left(\left(D_{i,t}-D_{i,t-1}\right)-\left(D_{i,t-1}-D_{i,t-2}\right)\right)\\&\quad+\left(\left(\varepsilon_{i,t}-\varepsilon_{i,t-1}\right)-\left(\varepsilon_{i,t-1}-\varepsilon_{i,t-2}\right)\right)\end{aligned}$$

This method allows us to neutralize the influence of the rate of wage growth of every individual to better assess the impact of training. The expectation of the wage growth of a trained individual will be calculated as follows:

$$E\left(\left(Ln\left(Wage_{i,t}\right)-Ln\left(Wage_{i,t-1}\right)\right)-\left(Ln\left(Wage_{i,t-1}\right)-Ln\left(Wage_{i,t-2}\right)\right)|D=1\right)>0$$

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:

$$E\left(\left(Ln\left(Wage_{i,t}\right)-Ln\left(Wage_{i,t-1}\right)\right)-\left(Ln\left(Wage_{i,t-1}\right)-Ln\left(Wage_{i,t-2}\right)\right)|D=0\right)=0$$

then we consider the change in wages only for the treatment group.

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, the demand for workers with low skills will decline and they will lose more wages than will more capable employees. Accordingly, assessment of the impact of training will be biased due to macroeconomic shocks.

We proceed to verify the hypothesis that the impact of 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]:

$$Q_{Ln(Wage_i)|X_i}(\theta)=X_i\beta_\theta,$$

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:

[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 *et al.*, 2002).

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

Thus, we can calculate estimates for each quantile. 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 quantile 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 – Higher School of Economics (RLMS-HSE).[8] The sample was formed for 9 years from 2003 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 2004 to 2008 (Figure 2).

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 and employees engaged in agriculture (about 0.1% of sample and their wage are formed in a special way).

As a result, the sample covered approximately 44,000 observations. The data base contains a question about 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 training.[9] Some training programs were fully or partially paid for by an employer, and others were paid for by employees. We exclude self-financing from our analysis because the question about 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 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 training in the previous period.[10] We use a question about the

[8] 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 http://www.hse.ru/rlms.

[9] *What is the source of funding for your additional training?*

[10] 1. The RLMS-HSE data does not allow to differentiate types of training, but contains the question about the number of days of training. But number of training days can not reflect the real length of training. We do not know the medium number of hours in each days of training. We cannot estimate the real intensity of training using the RLMS-HSE data because duration of 1 day of training may be 1 or 8 h.

2. Respondents may participate in several training throughout the year, but the RLMS-HSE data allows us to keep track of only one training (the most significant by respondent's opinion)

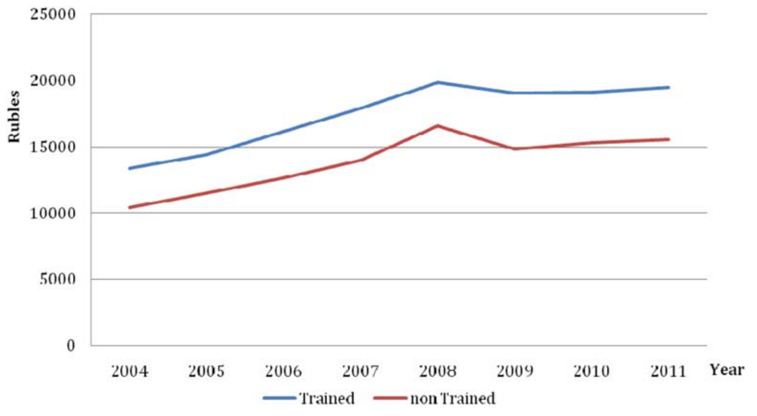

Figure 2: Wage trend (in 2011 prices).
Source: authors' calculations, RLMS-HSE, 2004–2011.

average wages for the year of the survey.[11] The information about the average wages for the year allows us to avoid seasonal bias or overstating due to a premium. To compare wages received in various periods, we deflate the wages (using CPI deflator) with respect to the 2011 year. The average wage of employees who participated in training programs is 26% more than the average wage of those who were not trained. Differences across the subsamples of respondents who did or did not receive training, in terms of wages and the control variables, are provided in Table 1.

One of the key moments of this study is to single out public sector workers (civil servants) from among all the respondents to compare the efficiency of vocational training among the sectors. Thus, the public sector is of interest for our study, as civil servants are obliged to complete training at least once every 3 years. There are currently over 14 million persons in Russia who work in the public sector, which makes up a considerable part of labour force. Yet the public and private sectors have different mechanisms of wage settings: the private sector establishes the wage level by market mechanism, whereas wage settings in the public sector in practice take place separately from the private sector, which results in wage 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; and (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%). 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) occupation and (3) type of activity.

Comparing groups of employees by their level of education, it should be noted that, according to researchers dedicated to the issue of 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

[11] *'Please specify your average monthly wage 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 wage 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 wage'.*

Table 1: *Descriptive statistics average 2004–2011*

	Mean value		Difference/(s.e.)
	Employees trained in the previous period	Non-trained employees	
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 old	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)
Tenure, years	10.1	7.6	2.473***/(0.230)
Occupation, %			
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)

Table 1: Continued

	Mean value		Difference/(s.e.)
	Employees trained in the previous period	Non-trained employees	
7. Transportation, Communication	7.7	9.3	−0.016**/(0.007)
8. Ministry of Internal Affairs, Security forces	4.5	4.8	−0.003/(0.005)
9. Management bodies	2.8	2.4	0.04/(0.004)
10. Education	24.6	10.1	0.145***/(0.008)
11. Science, Culture	3.2	3.6	−0.004/(0.005)
12. Health	17.1	8.5	0.086***/(0.007)
13. Trade, Domestic services	7.3	17.2	−0.099***/(0.010)
14. Finance	3.3	2.1	0.012***/(0.004)
15. Energy industry	3.3	1.7	0.016***/(0.003)
16. Housing and Community Services	2.7	3.7	−0.010***/(0.005)
17. 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, h	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 centre	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	47,896	

Source: RLMS-HSE, 2004–2011.
*significant at 10%.
**significant at 5%.
***significant at 1%.

with a tertiary level of education rises to 78%. The proportion of untrained employees with higher education hardly reaches 25%.

Occupation depends directly on an individual's level of education. Therefore, a high proportion of employees have undergone 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 training. One's occupation 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 occupations undergo training (see Table 1).

Results: the returns to training

The present section contains an estimation of the impact of training on wages using the OLS model and the method of double difference-in-differences. 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 2. The results suggest that wage gap between treatment and control group is about 16.2%.[12]

These results are quite consistent with the previous studies based on Russian data. For example, in the work of Berger *et al*. (2001), re-training increases wages by over 30%, whereas in the work of Lazareva (2006) the effect of training varies from 11% to 19%.

For the double difference-in-differences approach, we usedthe same vector of control variables as in the estimation with the OLS model. The estimate that was obtained in the analysis is 8.3%, which is approximately half of the assessment of the relevant period using the OLS model – 16.4% (see Table 2). 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 training on different subsamples using our data in the following two ways: (1) separately on the private and public sectors, as the value of 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 2 shows the results of the influence of training on wage in different subgroups using two methods: OLS and double difference-in-differences. The results received using the OLS method show that the estimation in the public sector equals that in the private sector (17.3% and 15.3%, respectively). The double difference-in-differences demonstrates that the estimation 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. 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 estimation 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 explained by differences in skill

[12] 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 $(e^{\gamma}-1)\times 100\%$ (Halvorsen & Palmquist, 1980).

Table 2: Comparison of the impact of training on wages using the OLS-model and the double difference-in-differences model

Sample	OLS (2004–2011)		OLS (2004–2008)		Double diff-in-diff (2004–2008)	
	Coefficient (%)/s.e.	Number of observations/ Adjusted R2	Coefficient (%)/s.e.	Number of observations/ Adjusted R2	Coefficient (%)/s.e.	Number of observations
Whole sample	*16.2****	*44,373*	*16.4****	*24,338*	*8.3****	*5053*
	(0.014)	*0.496*	*(0.020)*	*0.498*	*(−0.03)*	
Private sector	17.1***	34,040	17.3***	18,948	9.8***	3469
	(0.018)	0.522	(0.027)	0.490	(−0.042)	
Public sector	15.0***	10,333	15.3***	5390	5.1**	1307
	(0.019)	0.479	(0.028)	0.445	(−0.038)	
Without higher education	10.2***	31,822	9.1***	17,911	7.6*	3418
	(0.033)	0.48	(0.033)	0.452	(−0.044)	
With only higher education	18.7***	12,551	22.2***	6427	10.9***	1533
	(0.024)	0.437	(0.024)	0.478	(−0.043)	

Source: RLMS-HSE.
*significant at 10%.
**significant at 5%.
***significant at 1%.

levels. The double difference-in-differences method, which particularly minimizes the influence of skills on the estimation of training, reflects much less dissimilarity: 10.9% with higher education against 7.6% of others. Studies investigating the difference in effects of training between employees with different levels of education show that the increase in wages after training is higher for more educated workers (Bassanini *et al*., 2005; Evertsson, 2004; Finegold *et al*., 2005).

A comparison of the influence of 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 productivity 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. This means that the employer does not independently select the employee who can bring him or her the best return to training. Whether less skillful employees receive a payoff from training, let us proceed to the next stage of our analysis.

The results of the quantile analysis are presented in Figure 3, which reports quantile regression estimates for the 0.15, 0.25, 0.5, 0.75 and 0.85 quantiles. 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 unlogged wage as a dependent variable. The wages of the employees that received training in the first quantile were on average 1300 rubles higher then the wages of employees who did not. The third and fourth quantiles demonstrate little differences in returns, but the increase in the fifth quantile is most significant at a rate of approximately 2800 rubles.[13]

These results are consistent with the results of a study conducted by Abadie *et al*. (2002) based on U.S. data, which showed the largest relative increase in the first quantile, and that an increase in 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 $2058 (increase at a rate of 8%) in the fifth quantile.

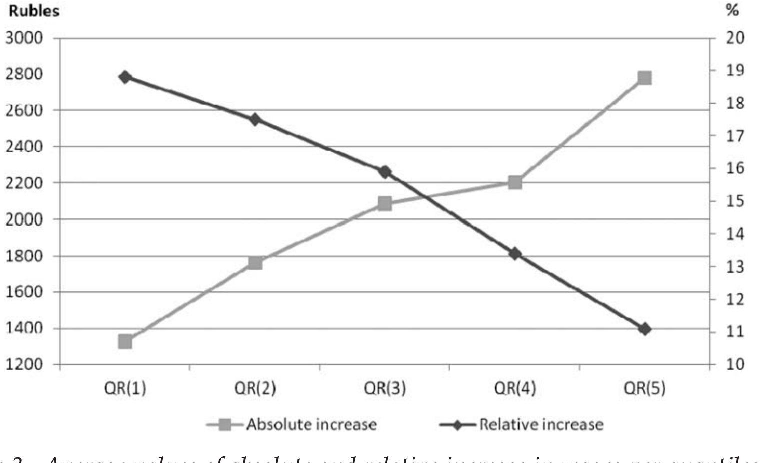

Figure 3: Average values of absolute and relative increase in wages per quantiles after training, RLMS-HSE, 2004–2011.

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

Conclusion

Analysis of the literature suggests that training positively affects productivity and wages. Moreover, the productivity gains are several times higher than the change in employees' wages (Ballot *et al*., 2006; Dearden *et al*., 2006). However, a number of factors may make it difficult to obtain an unbiased empirical estimation of the impact of training. For example, the abilities of employees (motivation, intelligence, communication skills and etc.) directly affect both the growth of wages and the returns to training. Apart from that, it is extremely difficult to measure such abilities and, consequently, to control them when carrying out the regression analysis.

The main purpose of this paper is to evaluate the rate of return to training for Russian workers. The existing estimates for Russia confirm the presence of returns to 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.

The wages of employees that received training are, on average, 24.9% 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 estimate the return to be 8.3%. Positive estimates obtained of the impact of training on wage increase correlate well with the results of previous studies. Our calculations show that when the unchanged characteristics in the period under investigation are controlled, the estimate of the effect is reduced almost twofold. Similar gaps in estimates for the OLS-model and the fixed-effects model have been demonstrated in a number of studies analyzing the impact of abilities on the effect of training (Bassanini *et al*., 2005; Loewenstein & Spletzer, 1999).

The key question of this study is whether there are any differences in the return to training for individuals with different levels of abilities. To obtain estimates, we divided workers into groups according to 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 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 to training, it should be noted that this return is positive and statistically significant. The results suggest that the employerdoes benefit from training of employees. After all, an increase in wages means an increase in labour productivity, and there is a large amount of empirical evidence suggesting that productivity growth is at least several times higher than the rate of wage growth (Ballot *et al*., 2006; Dearden *et al*., 2006). Finally, the employer does benefit from investments in employee training; otherwise, significant positive wage effects would be unlikely.

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Supporting Information

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