Working Paper 1: Returns to Education in the Russian Federation *

Ekaterina Melianova, Suhas D. Parandekar, Harry A. Patrinos, Artëm Volgin

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Abstract

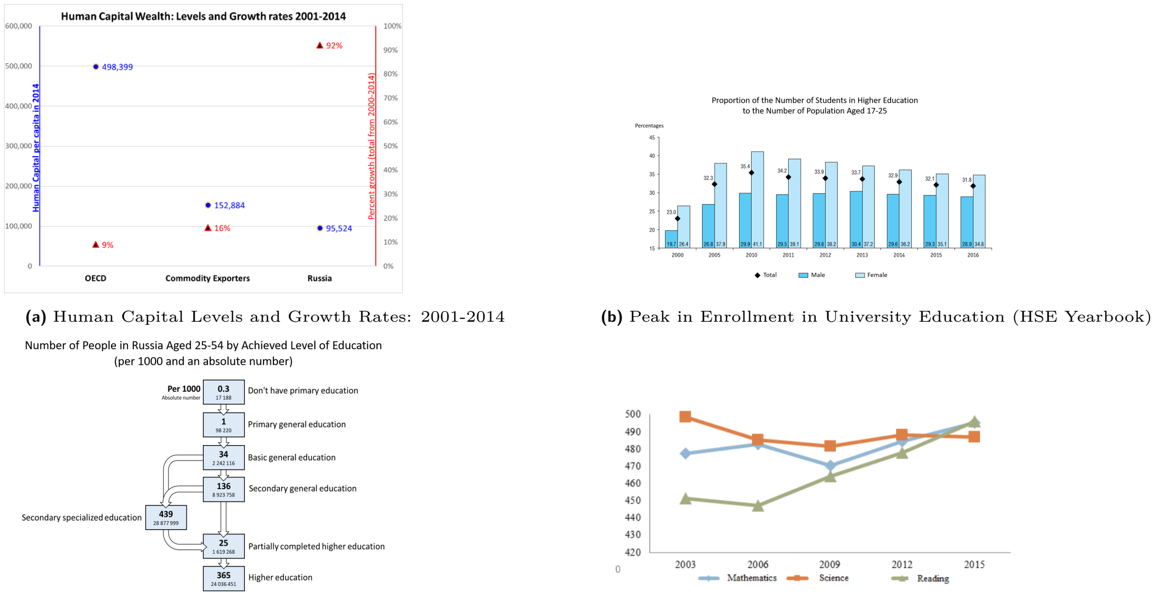
This paper investigates the returns to education for the Russian Federation from three perspectives. First, it reports the estimation of a Mincerian model and traces the evolution of returns to education in the period 1994-2018. The estimates show an increase in the returns in the first half of this period, followed by a gradual decline. Second, the paper explores the aspect of depreciation of human capital, a topic that has recently become salient because of the threat of automation. Depreciation follows a reverse trajectory, decreasing and them increasing, which may explain part of the observed tendency for the returns to education. Finally, the paper examines regional variation in the returns to education and finds a positive association between regional access to vocational education and the rate of return to education.

1 Returns to Education in the Russian Federation: Introduction

1.1 Motivation

The following set of four graphs set out the human capital challenge facing the Russian Federation. Figure 1.1a shows the extent of the gap in per capita human capital wealth between Russia and the OECD and difference in growth rates of per capita wealth in the period 2000-2014. Growth was ten times higher in Russia, though Figure 1.1a does not show annual rates.

*Arranged in alphabetical order of author last names. The entire code used to generate the graphs and tables presented in this paper is available on bitbucket at `https://bitbucket.org/zagamog/edreru/src/master/` , starting from the raw RLMS data graciously provided in the public domain by the National Research University-Higher School of Economics (HSE). Thanks are also due to Sylvain Weber for generously sharing the code from his University of Geneva Doctoral Thesis, which we adapted for one of the reported sets of estimations.



(a) Human Capital Levels and Growth Rates: 2001-2014

(b) Peak in Enrollment in University Education (HSE Yearbook)

(c) Labor Force Distribution by Educational Level (Rosstat)

(d) PISA Mean Scores for Russian Federation (OECD/PISA)

Figure 1.1: A set of stylized facts about Human Capital in the Russian Federation

Per capita wealth in Russia grew at an annual rate of 4.7% between 2000-2010 and then at a slower annual rate of 1.8% between 2010-2017, according to the World Bank report. Figure 1.1a shows that the per capita human capital wealth level at average for the OECD in 2014 was about USD 500,000 - five times that of Russia's 95,000 (measured in 2014 dollars). If Russia were to revert to the 2000-2010 level of growth of human capital, it would take about fifty years to catch up with the OECD; at the slower rate of growth of 1.8%, Russia would not be able to catch up even in one hundred years.

Figure 1.1b shows the percentage of 17-25-year-olds in the Russian federation enrolled in university programs. The figure shows that even as university enrollment had expanded very rapidly since 2000, when 23% of the age group were enrolled, university enrollment appears to have peaked and then declined. Women reached a peak of 41.1% enrollment in 2010 and had declined to 34.8% by 2016. Men reached a peak of 30.4% enrollment in 2013 and have declined more slowly to 28.9% in 2016. Every 0.1% of change is roughly equivalent to 120,000 individuals. Figure 1.1c indicates the educational attainment of the population segment 25 to 54 years (who would mostly have finished their formal education and within the retirement age - 55 for women until the recently introduced reforms). Figure 1.1c shows less than 14% of the labor force with final attainment of secondary general education (academic High School) - the main choice is between vocational education (nearly 45%) and university education (about 40%). Finally, Figure 1.1d shows that on cognitive attainment at Grade 9, Russian students are already at par with OECD students (PISA scores are designed with an OECD mean of 500); what comes in later education levels and the labor market is the crucial issue for convergence with OECD on human capital wealth levels.

A detailed analysis of the returns to education in the Russian Federation will provide insights into the stylized facts mentioned above. Together with other research being implemented by the World Bank and by researchers outside of the World Bank, the purpose of this analysis is to come up with a set of evidence based policy recommendations to enhance the human capital wealth of the Russian Federation.

1.2 Data

For country level analysis, we use the Russian Longitudinal Monitoring Survey (RLMS) - the only representative Russian survey with a sizable panel component allowing for a dynamic analysis (Kozyreva and Sabirianova Peter 2015). The data are notable for their reliability, diversity, and applicability to a variety of research questions. The RLMS embraces information on people's income and expenditure structure, their material well-being, educational and occupational behavior, health state and nutrition, migration, etc. RLMS sampling procedures have been thoroughly and extensively described elsewhere (Kozyreva and Sabirianova Peter 2015). The present research uses all 23 waves (1994 - 2018) that are available as of Wednesday 29$^{\text{th}}$ January, 2020. The sub-sample selected for empirical investigation in this paper consists of working individuals aged 25-64 who are out of school and have positive labor market experience and income.

1.3 Estimation

Our empirical analysis present results for the general working population of the Russian Federation aged 25-64 and by gender. We use a basic Mincerian specification shown in equation (1.1):

$$Log(Wage) = b_0 + b_1 \cdot Educ + b_2 \cdot Exp + b_3 \cdot Exp^2 + b_4 \cdot Gender + \epsilon \tag{1.1}$$

where $Log(Wage)$ is a logarithm of monthly wage, $Educ$ stands for the years of education or highest attained level of education, Exp and Exp^2 reflect the years of working experience and its quadratic term respectively, $Gender$ is a dummy variable for gender, b_0 is an intercept, $b_1 ... b_n$ are the respective slope estimates, ϵ refers to a normally distributed error term.

Dependent variable

For the dependent variable, we used the logarithm of an average monthly wage within the past year on a person's primary job (J13.2 variable in the RLMS dataset). If a person had an additional job, the maximum wage value among the two (J13.2 and J40) was selected for the analysis. In the waves from 1994 to 1996, the question mentioned above was absent; for those waves, we exploited a variable about the average amount of money earned by a respondent within the past 30 days (J10) as a reasonable approximation.

Independent variables

The present research uses both metric (measured in years) and categorical education variables. The metric version was created by assigning the average expected number of years corresponding to each attained education level. For the categorical version (EDUC), we distinguished three categories: *(1) secondary, (2) vocational, and (3) higher.* Incomplete levels were incorporated into the respective upper categories (e.g., incomplete higher - into higher). We are interested in exploring returns to education in general, and vocational and higher education. Estimations of premiums to primary and secondary schooling levels are technically unreachable to us since the number of adults without primary education, and the number of adults with only primary level is minuscule in the general population.

The experience variable was calculated as a difference between current age and years of education minus 6. Gender was included in the specification in the form of a dichotomous dummy variable with "1" standing for females, "0" - for males.

Figure 1.2 shows rates of overall and gender-wise returns to education in Russia in 1994-2018: percentage increment in a person's earnings due to one additional year of schooling (exact estimation results available on github site for this paper). Overall, one can notice a moderate curved growth in returns to education in Russia, achieving its peak in the early 2000s, which is followed by a downward pattern. Education payoffs for women are higher than those of men, but the difference appears to have narrowed in recent years (see tables with 95% confidence intervals of regression coefficients on gihub site for this paper).

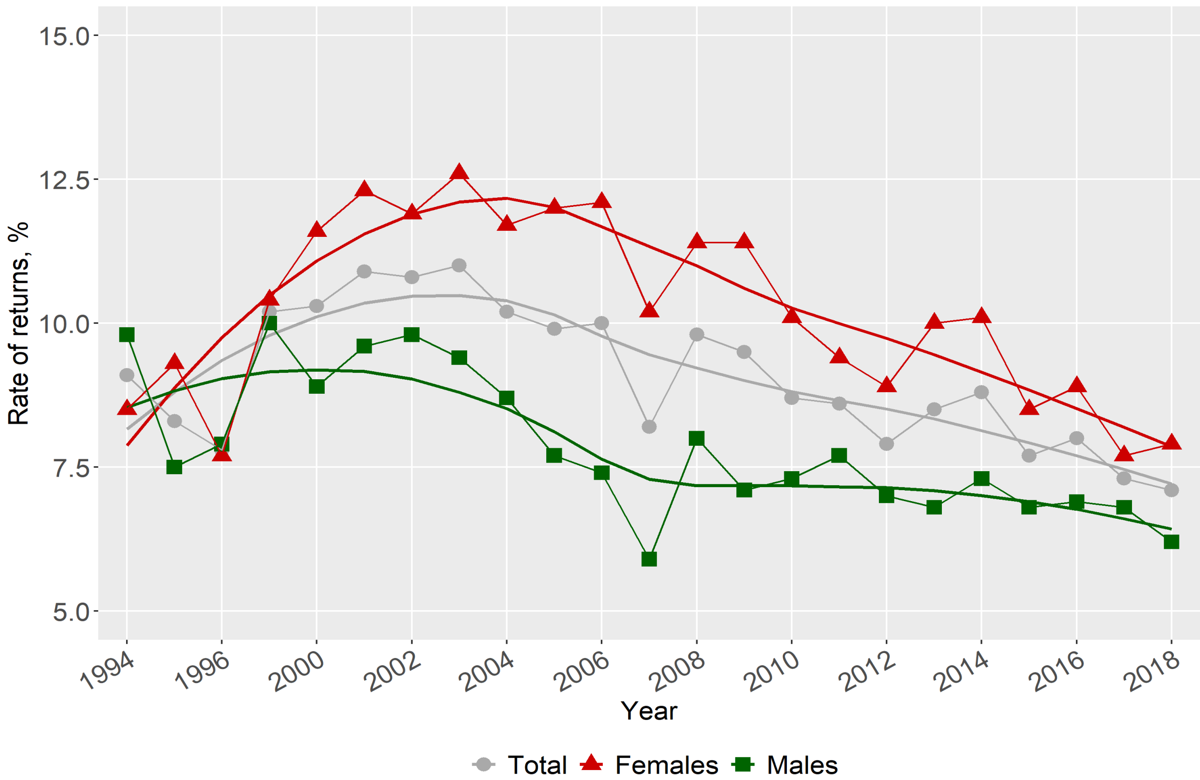


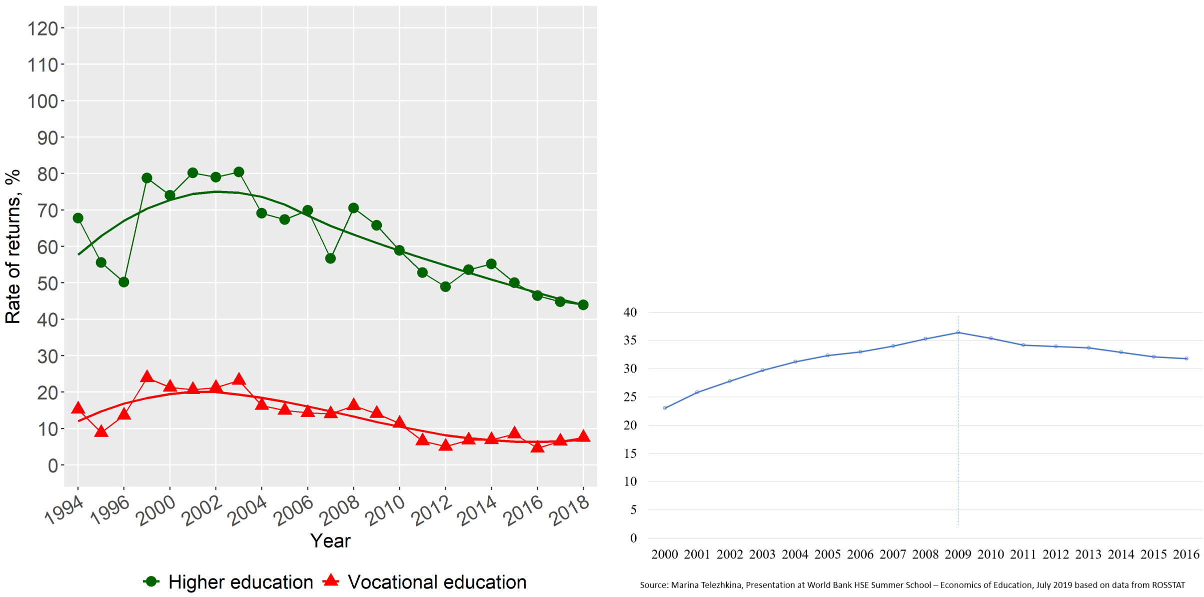
Figure 1.2: Rates of Returns to Education in Russia, RLMS 1994-2018

We are particularly interested in the returns to specific levels of education, estimated through a series of dummy variables. Using Secondary Education completed as the base or omitted dummy for purpose of interpretation, we use dummies for Vocational Education and for Higher Education. The specification is presented in equation (1.2):

$$Log(Wage) = a_0 + a_1 \cdot D_{Voc} + a_2 \cdot D_{Higher} + a_3 \cdot Exp + a_4 \cdot Exp^2 + a_5 \cdot Gender + \epsilon \tag{1.2}$$

Figure 1.3, panel (a) displays rates of returns to Higher and Vocational education (as compared to Secondary education) in Russia for the period 1994-2018. The results suggest that on average wage premiums to university education in Russia are roughly 3-5 times greater than to vocational schooling. The observed trend for premiums to both Vocational and Higher education levels is similar to the trend for education in general with the following peaks: 83% for Higher education and 26% for Vocational education compared to the average earnings of workers with a Secondary education. The interesting pattern to note from panel 1.3a is the apparent co-movement of vocational education and higher education - the higher education smoothing curve turns a bit more sharply than the one for vocational education, but their movement is matching, even at second-order levels of smoothness. Further, even though higher education premium remains much above the premium for vocational education, there is a perceptible narrowing of the difference in recent years. Panel 1.3b, which is drawn from a presentation made by Marina Telezhkina at the WB-HSE Summer School on the Economics of Education in July 2019, shows the interesting pattern of higher education enrollment rates for the population of 17-25 year old. Panel 1.3b shows the downturn in returns reflected in enrollments, with the peak in enrollments coming about 10 years later.

Figure 1.3: Rates of Returns to Higher and Vocational Education in Russia, RLMS 1994-2018

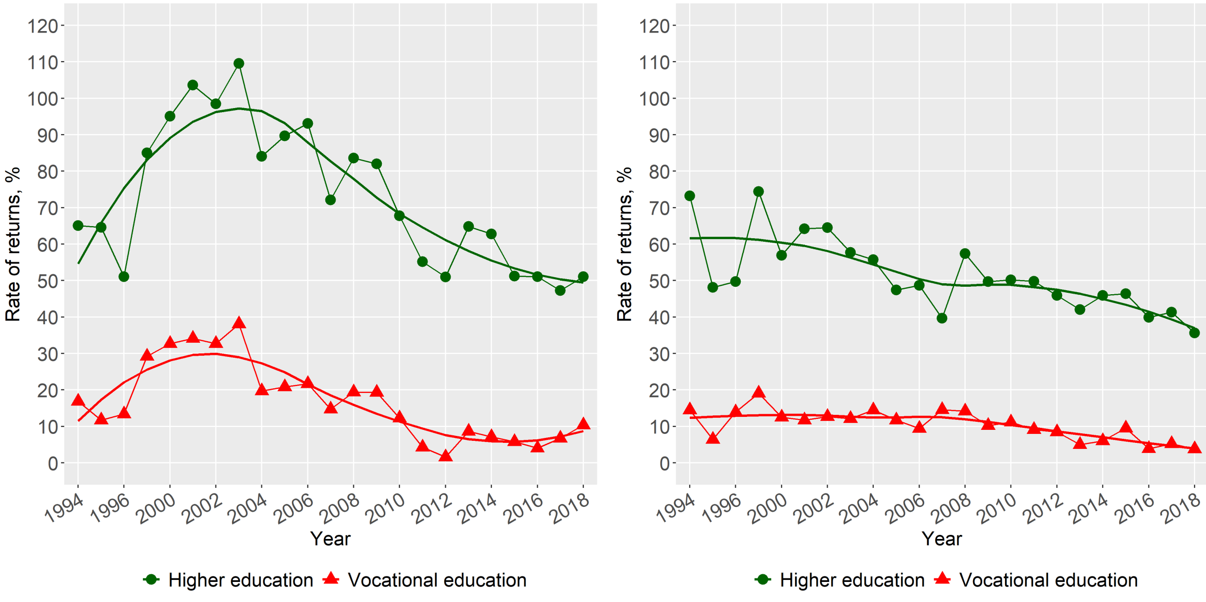


(a) Rates of Return

(b) Enrollment in Higher Education

When estimated separately by gender, we find trend variation by gender. The results from estimation of earnings functions show that payoffs to Higher education for males varied from 45% to 76%, whereas women's returns are described by an inversely U-shaped pattern, reaching their maximum of 104% in 2001. Within roughly the last 5 years, wage premiums to higher education for women have stabilized around the level of men (50%). Gender wise enrollment rates in higher education (not shown) ten years later appears to match the differences in rates of return, strengthening the hypothesis that market rates of return to education in Russia do indeed influence individual continuing school decisions.

A similar comparative picture is observed with respect to vocational education, albeit with a different kind of variation by gender (see Figure 1.4): returns for males are almost flat within the time period while returns for females shows a concave pattern. The overall outcome concerning payoffs to schooling isolated by gender has been confirmed in a similar fashion by past studies (e.g., Cheidvasser and Benítez-Silva 2007).



(a) Females

(b) Males

Figure 1.4: Rates of Returns to Higher and Vocational Education in Russia, RLMS 1994-2018

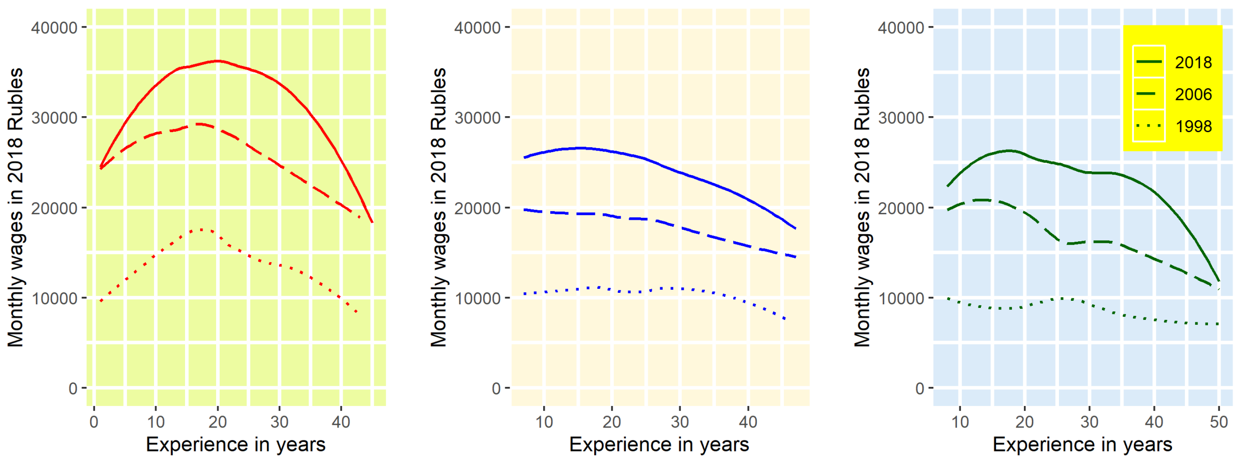
2 Depreciation of Human Capital in the Russian Federation

Age-earnings profiles are almost invariably concave downward shaped. Earnings rise after a labor market entrant completes full-time schooling. The profile indicates a peak in earnings, usually a few years before retirement, after which there is a steady decline in earnings. The concave shape is an outcome of two countervailing tendencies - the rise attributed to continued accumulation of human capital through training and the decline due to depreciation. The precise shape and location of the peak is an object of analytical interest. Depreciation of human capital is useful to investigate from a policy perspective. Just like some physical capital (machinery, buildings) are built stronger and last longer, is it possible that some kinds of education inherently generate human capital that is slower to depreciate? What attributes of the labor market lead to lower or higher levels of depreciation? What about the welfare implications of changes in the age at which individuals retire from the labor force? How has the depreciation rate of human capital changed over time in the Russian Federation? In particular, can changes in the rate of depreciation explain the observed pattern of the rates of return depicted in 1.2?

2.1 Analytical Treatment of Depreciation

Rosen (1976) and Mincer and Ofek (1982) presented early treatments on the depreciation of human capital. However, in terms of a focus on depreciation, a seminal paper of Neuman and Weiss (1995) established the basic parameters that have guided the research since that time. The authors introduce the important distinction between two kinds of depreciation or loss of productive potential of human capital. The first one, termed as “obsolescence" or “vintage effect", is due to an overall upgrading of technology or the operation of other market forces that lowers the value of education or training obtained in a previous period. This is also termed as an ‘external depreciation", presumably as it is a given for an individual. The second kind of depreciation is attributed to the deterioration of physical and mental abilities of an individual due to the progression of a person’s age, or the simple passage of time. This is also termed as “internal depreciation". Neuman and Weiss posited that external effects would be more important for higher levels of education, under the assumption that changes in the labor market are transmitted more readily to higher education. They give the example that a recently educated electrical engineer would be learning many new things compared to one who studied the same subject in an earlier time. Neuman and Weiss reasoned that workers with basic education levels may not suffer as much from obsolescence.

Figure 2.1 shows for the Russian Federation the effects described by Neuman and Weiss. There are three panels in the figure, and three lines in each figure. The vertical axis indicates the monthly earnings in constant 2018 rubles, using the Rosstat CPI deflator. The horizontal axis indicates the years of experience. The dotted line shows the earnings for 1998, the dashed line represents 2006 and the solid line the data from 2018. Each of the panels, representing a different level of education, shows an upward drift in the experience-earnings profiles in the period from 1998 to 2018. Only Figure 2.1a shows a clear concave downwards profile for Higher Education; the concave tendency is less pronounced for the other two levels of Vocational education and Secondary education.



(a) Higher Education **(b)** Vocational Education **(c)** Secondary Education

Figure 2.1: Neuman-Weiss vintage effects by education level from RLMS Rounds 1998, 2006 and 2018

Putting the curves together by year (Figure 2.2)suggests that the premium for university education over the other two levels does narrow at higher levels of experience. In the figure, to accomodate the relatively lower wage levels of 1998, the leftmost panel (Figure 2.2a) is slightly compressed compared to the other two panels. The converging tendency between levels of education would suggest that depreciation is indeed higher for university graduates. In the next two subsections, we present a more rigorous quantitative treatment of this issue, using a variant of Neuman-Weiss developed by Murillo (2006) and an alternative approach developed by Arrazola et al. (2005).

(a) 1998 (b) 2006 (c) 2018

Figure 2.2: Neuman-Weiss vintage effects by Year from RLMS Rounds 1998, 2006 and 2018

2.2 Differential Depreciation Affecting Education and Training

Murillo (2006) implemented a variation of the Neuman and Weiss model with a focus on empirical implementation to Spain. We follow the Murillo notation in the implementation of the model, which begins with the following earnings equation:

$$log(W_T) = \alpha + \beta_1 KS_T + \beta_2 KE_T \tag{2.1}$$

where W represents earnings, KS the stock of human capital derived from schooling of S years, and KE the stock of human capital acquired from on the job training or experience, and T indexes the number of experience years since completing formal education. In this set-up, the parameters β_1 and β_2 are the productivity parameters for the respective parts of the stock of human capital. Both are assumed to suffer from depreciation or the loss of productive value. At this stage, we do not distinguish between the causes (internal or external) of this loss. The path of the stock of human capital due to education is given by

$$KS_T = S + hTS \tag{2.2}$$

where h is the rate of loss of the stock. The next equation for the loss of stock gained from experience is a bit more complicated. The stock from schooling, S is taken to be fixed at the end of the full-time schooling period and the beginning of the working period. However, experience is being built up every year at the same time as the capital acquired from previous experience depreciates.

$$KE_T = \{1 + (T-1)\cdot\gamma\} + \{1 + (T-2)\cdot\gamma\} + \{1 + (T-3)\cdot\gamma\} + \ldots + \{1\} \tag{2.3}$$

where γ is the rate of loss applied every year. The equation can be simplified and summarized as

$$KE_T = T + \gamma\cdot\{(T-1) + (T-2) + (T-3) + \ldots + 1\} = T + \gamma\cdot\frac{T^2}{2} \tag{2.4}$$

Substituting equations 2.2 and 2.4 into equation 2.1, we get

$$log(W) = \alpha + \beta_1 S + \beta_1 hTS + \beta_2 T + \frac{\beta_2\gamma}{2}T^2 = \alpha + \beta_1 S + \pi_1 TS + \beta_2 T + \pi_2 T^2 \tag{2.5}$$

where $\pi_1 = \beta_1 h$ and $\pi_2 = \frac{\beta_2\gamma}{2}$. From 2.5, the depreciation rate during T years applied to schooling can be computed as $\pi_1 S$ and the depreciation rate applied to experience as $2\pi_2 T$.

Estimation Results

Table 2.1 shows OLS estimation results of equation 2.5 run on the whole sample of the RLMS observations. In this subsection, we analyzed separately six years that represent the ends (1994 and 2018), the diffused peak (2003 and 2006), and halfway points to the ends (2012 and 2003) of the available time interval. The idea is to examine the role played by changes in depreciation to explain the observed pattern of variation in the rates of return shown in Figure 1.1.

Table 2.1: Results of Estimating Human Capital Depreciation for the Whole Sample, RLMS

	1994	**1998**	**2003**	**2006**	**2012**	**2018**
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	10.266***	4.720***	6.762***	7.854***	8.889***	9.205***
	(0.301)	(0.258)	(0.221)	(0.181)	(0.128)	(0.158)
Educ, years (S)	0.113***	0.116***	0.094***	0.074***	0.054***	0.053***
	(0.020)	(0.017)	(0.015)	(0.012)	(0.008)	(0.010)
Educ X Exper (TS)	−0.001*	−0.001*	−0.00005	0.0003	0.0003	0.0001
	(0.001)	(0.001)	(0.001)	(0.0005)	(0.0003)	(0.0004)
Exper(T)	0.053***	0.044***	0.016	−0.001	0.012*	0.023***
	(0.015)	(0.013)	(0.011)	(0.009)	(0.007)	(0.008)
Exper squared (T^2)	−0.001***	−0.001***	−0.0004***	−0.0002*	−0.001***	−0.001***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	3,037	3,100	3,856	4,800	7,417	6,112
R^2	0.043	0.058	0.068	0.078	0.088	0.071
Adjusted R^2	0.042	0.057	0.067	0.077	0.087	0.071
Residual Std. Error	0.934	0.800	0.782	0.715	0.666	0.617
F Statistic	34.062***	47.678***	69.846***	101.053***	177.952***	117.104***

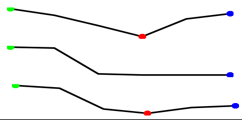
Note: *p<0.1; **p<0.05; ***p<0.01

Using the coefficient estimates derived from Table 2.1, we compute the depreciation rate during T years applied to schooling as $\pi_1 S$ and the depreciation rate applied to experience as $2\pi_2 T$, evaluating the expression at the mean level of schooling. Table 2.2 reports the depreciation rate values so calculated with the corresponding sample means. The table shows an interesting U-shaped pattern in the depreciation rate for human capital, attributable mainly to the depreciation rate associated with experience. The depreciation rate associated with education has been declining steadily and did not pick up again as measured with the given data. The depreciation rate associated with experience declined at first and then picked up again.

Table 2.2: Average Depreciation Rate by Years

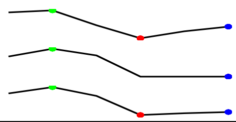
Panel A: Whole Sample

	Statistic	1994	1998	2003	2006	2012	2018
1	Experience, mean	21.41	22.32	22.20	22.24	22.52	22.52
2	Education, mean	12.70	12.69	12.79	12.79	12.95	13.27
3	DR Experience, %	1.87	1.55	1.04	0.50	1.37	1.63
4	DR Education, %	2.80	2.71	0.11	0.00	0.00	0.00
5	DR Human Capital, %	4.67	4.26	1.15	0.50	1.37	1.63



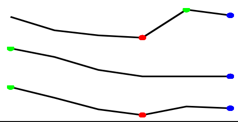
Panel B: Female Sample

1	Experience, mean	21.36	22.09	22.34	22.33	22.69	22.67
2	Education, mean	12.76	12.85	12.98	13.05	13.24	13.58
3	DR Experience, %	2.46	2.57	1.62	0.78	1.23	1.52
4	DR Education, %	3.81	5.31	3.97	0.00	0.00	0.00
5	DR Human Capital, %	6.27	7.88	5.59	0.78	1.23	1.52



Panel C: Male Sample

1	Experience, mean	21.47	22.58	22.02	22.14	22.31	22.34
2	Education, mean	12.62	12.50	12.57	12.47	12.61	12.91
3	DR Experience, %	1.83	1.08	0.80	0.67	2.23	1.91
4	DR Education, %	3.96	2.74	0.91	0.00	0.00	0.00
5	DR Human Capital, %	5.78	3.82	1.71	0.67	2.23	1.91



Further work is required, including computation of the depreciation rates at levels other than the mean values. At this stage, the findings raise some interesting questions which needs to be addressed by further research. In the period from 1994 to 2006, the depreciation rate appears to be declining, just as the rates of return were on an ascending curve. As both kinds of depreciation (for experience and education) were declining, it is possible that the main cause was in the labor market experience rather than in the education system. Since the peak of earnings premiums in the 2003-2006 period, as returns to education have declined, we see that the depreciation rates associated with experience have started climbing back, but depreciation rates associated with education have declined to null and not reverted. It is tempting to claim that this indicates a qualitative improvment in the skills provided by the education system, but further investigation is warranted before making such a claim. We explore next an alternative computation of the depreciation rate.

2.3 Depreciation of Human Capital using Non-Linear Least Squares

Arrazola et al. (2005) developed an alternative approach the issue of human capital depreciation with a first principles approach regarding the formation of human capital, providing an empirical estimation for Spain. A number of other authors have replicated Arrazola's approach. In this paper, we follow the notation adopted by Sylvain Weber, who estimated depreciation rates for Switzerland (Weber (2008) and Weber (2011)). Weber starts with the definition of s_t – the time fraction invested into the generation of new human capital by a person at age t. Relying on a human capital theory implication about the decline of s_t over the life cycle, Weber shows that the complete path of s_t is written as follows:

$$s_t = \begin{cases} 0 & \text{if } t < 6 \\ 1 & \text{if } 6 \leq t < S^\star \\ \alpha - \frac{\alpha}{T-S^*} \cdot (t - S^\star) = \alpha \cdot \left(1 - \frac{X_t}{L}\right) & \text{if } S^\star \leq t \leq T \end{cases} \tag{2.6}$$

where α is a parameter, S^* is the age when schooling life ends and the working one begins, T is the retirement age, $L = T - S^*$ is the total working life length, $X_t = t - S^*$ is experience. Schooling duration is equal to $S^* - 6$.

The model then utilizes the standard human capital theory specification that potential earnings E_t are exponentially related to the human capital stock:

$$E_t = W \cdot \exp\left(\beta_K K_t + \beta_Z Z_t\right) \tag{2.7}$$

where W is a return per period on a unit of earnings capacity, K_t is the stock of human capital at time t, Z_t is a set of observable attributes supposed to influence on earnings, and K, Z are the parameters of interest. The stock of human capital in period t can be estimated as the sum of the stock from the previous period minus the loss due to depreciation plus the quantity generated during the t_{th} period:

$$K_t = K_{t-1} - \delta \cdot K_{t-1} + \Delta K_t = (1-\delta) \cdot K_{t-1} + \Delta K_t \tag{2.8}$$

By recursion, an expression for K_t as a function of the human capital stock acquired at the end of formal education K_S is given by:

$$K_t = (1-\delta)^t \cdot K_S + \sum_{j=S^*}^{t-1} (1-\delta)^j \cdot \Delta K_{t-j} \tag{2.9}$$

Taking the logarithms of the expression 2.7 and substituting K_t by the equation 2.9 leads to:

$$\ln E_t = \ln W + \beta_K \cdot \left\{ (1-\delta)^t \cdot K_S + \sum_{j=S^*}^{t-1} (1-\delta)^j \cdot \Delta K_{t-j} \right\} + \beta_Z Z_t \tag{2.10}$$

Next is the standard human capital relationship between observed and potential earnings. As only a proportion of s_t of the human capital stock is used in the actual production of earnings, observed earnings can be expressed by:

$$\begin{aligned} Y_t &= (1 - s_t) \cdot E_t \\ \ln Y_t &= \ln (1 - s_t) + \ln E_t \end{aligned} \tag{2.11}$$

Combining 2.10 and 2.11 results in:

$$\ln Y_t = \ln W + \beta_K \cdot \left\{ (1-\delta)^t \cdot K_S + \sum_{j=S^*}^{t-1} (1-\delta)^j \cdot \Delta K_{t-j} \right\} + \beta_Z Z_t + \ln (1 - s_t) \tag{2.12}$$

Finally, as the human capital stock at the end of education is related to the human capital received, there is a direct association between this stock and the schooling duration:

$$K_S = S \tag{2.13}$$

The production of new human capital K_t depends on the portion of time devoted to this activity:

$$\Delta K_t = s_t = \begin{cases} 0 & \text{if } t < 6 \\ 1 & \text{if } 6 \leq t < S^\star \\ \alpha \cdot \left(1 - \frac{X_t}{L}\right) & \text{if } S^* \leq t \leq T \end{cases} \tag{2.14}$$

Using 2.8 and 2.11 to express K_S as a sum of the human capital quantities produced during schooling, the result is:

$$K_S \overset{(3)}{=} \sum_{j=0}^{S^*} (1-\delta)^j \cdot \Delta K_{S^*-j} \overset{(9)}{=} \sum_{j=6}^{S^*} (1-\delta)^j \tag{2.15}$$

Substituting 2.13 and 2.14 into 2.12, adding an error term and an individual subscript i provides the equation that can be estimated using non-linear least squares (NLS):

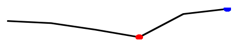
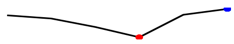
$$\begin{aligned} \ln Y_{it} = \ln W + \beta_K \cdot \Bigg\{ (1-\delta)^{X_{it}} \cdot S_i + \alpha \cdot \frac{1 - (1-\delta)^{X_{it}}}{\delta} \cdot \\ \left(1 + \frac{1-\delta}{\delta \cdot L_i}\right) - \frac{\alpha \cdot X_{it}}{\delta \cdot L_i} \Bigg\} + \ln \left\{ 1 - \left(\alpha - \frac{\alpha}{L_i} \cdot X_{it} \right) \right\} + \beta_Z \cdot Z_{it} + u_{it} \end{aligned} \tag{2.16}$$

where t shows a time period, $\ln Y$ is a logarithm of the observed earnings, $\ln W$ is a logarithm of a return per certain period on a unit of earnings capacity, β_K is the effect of the human capital stock on earnings, β_Z is the effect of other covariates in the model on earning, δ is the human capital depreciation rate, X_{it} is the labor market experience, L_i is the total working life length, α is a parameter reflecting the share of time invested in training, Z_{it} is a set of observable attributes hypothesized to have an impact on earnings, u_{it} is an error term.

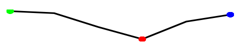
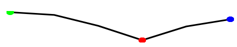
Table 2.3 reports empirical findings for the estimation of the 2.16 equation using NLS with robust standard errors for the same range of years as presented in the previous section. Unlike that earlier model, the Arrazola model does not allow for a different treatment of depreciation of human capital acquired from schooling or from experience - only a single δ (depreciation rate of the human capital) parameter is estimated. However, the model does allow the identification of an α parameter (related to post-school investment in human capital).

Table 2.3: Non-Linear Lest Squares estimated for range of years

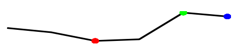
Panel A: Whole Sample

Parameter	1994	1998	2003	2006	2012	2018	
lnW	10.4780	4.8622	6.7305	7.8405	8.4104	8.8524	
	(0.1913)	(0.1646)	(0.1409)	(0.0838)	(0.0787)	(0.0885)	
bk	0.1453	0.1429	0.1144	0.0723	0.1382	0.1487	
	(0.0167)	(0.0144)	(0.0140)	(0.0106)	(0.0087)	(0.0086)	
delta	0.0246	0.0208	0.0093	-0.0040	0.0369	0.0459	
	(0.0052)	(0.0043)	(0.0050)	(0.0058)	(0.0043)	(0.0051)	
alpha	0.4798	0.3860	0.1352	-0.1690	0.4972	0.6686	
	(0.0912)	(0.0790)	(0.0911)	(0.0950)	(0.0601)	(0.0533)	
Sample size	3037	3100	3856	4800	7417	6112	

Panel B: Female Sample

Parameter	1994	1998	2003	2006	2012	2018	
lnW	10.1580	4.1353	5.7238	6.9251	7.9143	8.4131	
	(0.2447)	(0.2124)	(0.1973)	(0.1663)	(0.1136)	(0.1275)	
bk	0.1524	0.1818	0.1702	0.1321	0.1329	0.1330	
	(0.0196)	(0.0163)	(0.0158)	(0.0149)	(0.0104)	(0.0103)	
delta	0.0275	0.0260	0.0156	0.0065	0.0197	0.0249	
	(0.0060)	(0.0042)	(0.0038)	(0.0044)	(0.0036)	(0.0036)	
alpha	0.5889	0.5408	0.3466	0.0900	0.3354	0.4628	
	(0.0974)	(0.0749)	(0.0763)	(0.0862)	(0.0659)	(0.0609)	
Sample size	1645	1667	2093	2630	4057	3312	

Panel C: Male Sample

Parameter	1994	1998	2003	2006	2012	2018	
lnW	10.4992	5.1267	7.3195	8.1556	8.2117	8.8384	
	(0.2880)	(0.2420)	(0.1530)	(0.1158)	(0.1195)	(0.1213)	
bk	0.1697	0.1425	0.0845	0.0725	0.2206	0.1784	
	(0.0244)	(0.0215)	(0.0180)	(0.0163)	(0.0111)	(0.0118)	
delta	0.0261	0.0168	-0.0020	0.0015	0.0595	0.0511	
	(0.0067)	(0.0059)	(0.0082)	(0.0095)	(0.0063)	(0.0069)	
alpha	0.4625	0.2669	-0.1351	-0.1196	0.8161	0.7312	
	(0.1278)	(0.1162)	(0.1362)	(0.1475)	(0.0484)	(0.0663)	
Sample size	1392	1433	1763	2170	3360	2800	

The sparklines in Table 2.3 indicates a smilar roughly U-shaped pattern for depreciation as reported in Table 2.2, with depreciation of human capital first declining and then increasing again. This supports the narrative that the observed increase and then decrease in returns to education in the Russian Federation may be explained through the effect of depreciation. The exact magnitudes of estimated depreciation in the two tables do not match - while the range of depreciation is similar - between 2% to 5%, the 2018 figures indicate a higher level in Table 2.3.

An intriguing finding concerns the difference in depreciation rates between female and male workers. The conventional human capital logic holds that women typically face longer periods outside of the labor market because of child-bearing and child-rearing responsibilities. Absence from the labor market would lead to higher levels of depreciation amongst women. In the case of the Russian Federation, the estimates of both Table 2.2 and Table 2.3 reflect this pattern in the first half of the period, up until the estimates for 2006. Around the time of the peak in returns, the depreciation rate drops to zero for both men and women, but in the subsequent period, the depreciation rate for men appears to be higher than the rate for women. The fact that both methodologies reflect this pattern indicates a real phenomenon, rather than a statistical artefact, and something to be explored further.

Finally, a word about the α parameter, which is an indicator of post-schooling investment in human capital. This parameter also shows a similar tendency as the depreciation rate, meaning a decline to zero and a subsequent increase. As with depreciation, the first half shows a higher α for female workers until it drops to zero for both males and females at the time of peak returns, and in the subsequent period the α parameter level is higher for males.

Adapting a strategy adopted by (Weber (2008) to fit the Russian context, Table 2.4 provides four alternative specifications displayed separately by gender. The four models portray the following combinations regarding the α and δ parameters: *model I* - both α and δ are constant across education levels; *model II* - α is constant, δ varies; *model III* - α varies, δ is constant, *model VI* - both α and δ vary across education levels.

Model I - the base model, has already been presented in Table 2.3 and is shown again as part of Table 2.4 only for easy reference. Model II, allows the δ parameter to vary across education levels; Model III allows the α parameter to vary across education levels; and finally Model IV allows both parameters to vary by education level. The estimates indicate the absence of depreciation effects by educational level. Weber had found for Switzerland that depreciation is higher for vocational education, and provided the explanation that vocational education skills tend to be more specific to jobs and careers. However, this finding is not replicated with the data for the Russian Federation. The statistically signifciant finding in Table 2.4 concerns the α parameter. Post-schooling investment in human capital for those with vocational education is not different from those with secondary education, but university education brings with it a higher level of the α parameter, for both male and female workers.

Table 2.4: Empirical Estimates for Females and Males, RLMS 2018

	Females				Males			
	I	II	III	IV	I	II	III	IV
lnW	8.413***	8.901***	8.778***	8.644***	8.838***	8.950***	9.022***	8.864***
	(0.127)	(0.319)	(0.0975)	(0.279)	(0.121)	(0.291)	(0.0925)	(0.221)
bk	0.133***	0.111***	0.125***	0.129***	0.178***	0.177***	0.183***	0.179***
	(0.0103)	(0.0115)	(0.0105)	(0.0130)	(0.0118)	(0.0147)	(0.0122)	(0.0111)
delta	0.0249***				0.0511***			
	(0.00357)				(0.00692)			
alpha	0.463***	0.553***			0.731***	0.761***		
	(0.0609)	(0.143)			(0.0663)	(0.124)		
delta_base		0.0387*	0.0355***	0.0305*		0.0558**	0.0597***	0.0431**
		(0.0181)	(0.00453)	(0.0134)		(0.0185)	(0.00506)	(0.0144)
delta_voc		-0.00109		-0.00128		0.000258		0.00694
		(0.00251)		(0.00519)		(0.00150)		(0.00547)
delta_uni		-0.00699		0.00198		-0.00143		0.00892
		(0.00610)		(0.00805)		(0.00333)		(0.00728)
alpha_base			0.448***	0.424*			0.698***	0.498**
			(0.0728)	(0.172)			(0.0578)	(0.166)
alpha_voc			0.0124	-0.0322			0.00828	0.144
			(0.0442)	(0.128)			(0.0381)	(0.114)
alpha_uni			0.208***	0.206			0.157***	0.307*
			(0.0533)	(0.134)			(0.0420)	(0.125)
N	3312	3312	3312	3312	2800	2800	2800	2800
adj.R^2	0.082	0.085	0.091	0.091	0.096	0.096	0.106	0.107
AIC	6017.6	6006.2	5983.5	5987.1	4842.8	4844.9	4813.7	4814.6
BIC	6042.0	6042.8	6020.2	6035.9	4866.5	4880.5	4849.3	4862.1

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3 Further Exploration of Depreciation

3.1 Depreciation and the Gender dimension

The previous section indicated an intriguing finding regarding depreciation and gender, with recent rounds of RLMS data indicating a higher level of depreciation for male workers, a possibly anamolous finding. This sub-section draws upon the literature regarding occupational gender segregation, the tendency for some jobs to be dominated by one gender, a phenomenon that has been studied in detail in labor markets around the world (Preston (1999) and Blau, Brummund, and Liu (2013)). Empirical application in the Russian Federation has examined trends regarding gender segregation in occupations (Klimova (2009),Klimova and Ross (2012),Kosyakova, Kurakin, and Blossfeld (2015)). The bulk of this literature is concerned with the issue of the possible inequities and inefficiencies arising from gender segregation. However, for purpose of this paper is to exploit the presence in the data of occupational gender segregation to obtain insights into human capital depreciation.

In this section,we extend the Neuman and Weiss model of the previous section to compare the estimated depreciation rates between female- and male-dominated groups in various industries and occupations. The RLMS 2018 database contains information about sector or industry and standardized ISCO-08 classfication of jobs. These were used to tag gender-based industrial sectors and occupations, respectively. The average female representation by sector was 54%. Using a range of ± 10% from the average, a sector was marked as female-dominated if it contained more than 64% of women workers, and male-dominated if it contained less than 44% of women workers. Neutral sectors occupied the middle of the distribution. Figure 3.1 visualizes this procedure; Table 3.1 maps title of sectors with female percentages in them. To generate gender-related occupations a similar tactic was applied based on the 2-digit ISCO-08 classification (see Figure 3.2 and Table 3.2).

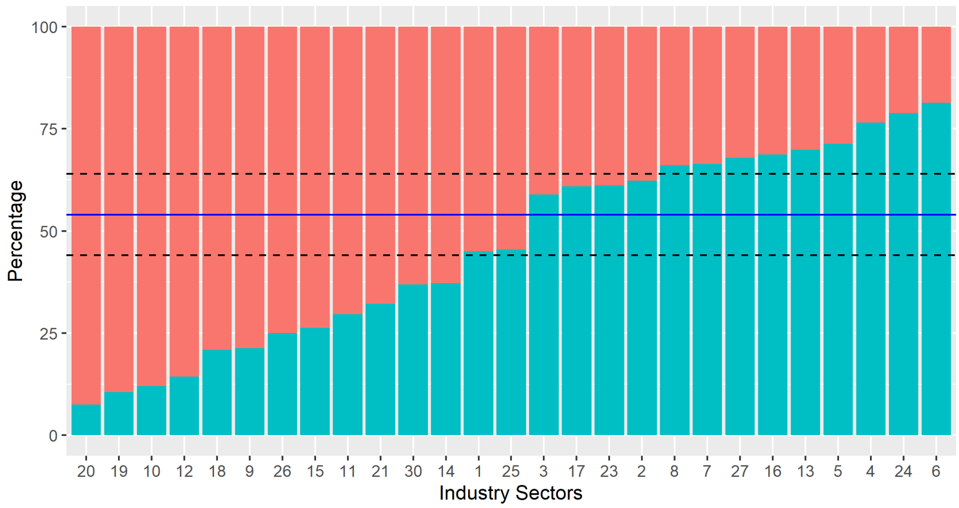


Figure 3.1: Distribution of Employment in RLMS 2018 by Industry and Gender

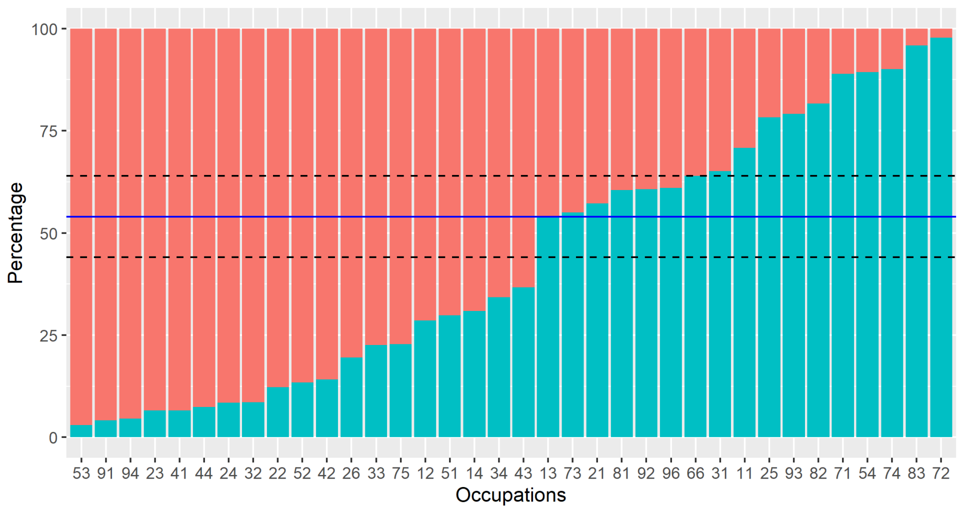


Figure 3.2: Distribution of Employment in RLMS 2018 by Occupation and Gender

Table 3.1: Industries by Strength of Female Proportion, RLMS 2018

Category	Sector	N fem	% fem	N total
Female dominated	Social Services	37	92.5%	40
	Other	17	89.5%	19
	Education	609	88.0%	692
	Public Health	412	85.7%	481
	Real Estate Operations	19	79.2%	24
	Government and Public Administration	155	78.7%	197
	General Public Services	15	75.0%	20
	Finance	107	73.8%	145
	Science, Culture	100	70.4%	142
	Jurisprudence	19	67.9%	28
Neutral	Mass Media, Telecommunications	24	63.2%	38
	Trade, Consumer Services	738	62.8%	1175
	Light industry, Food industry	209	55.0%	380
	Sports, Tourism,Entertainment	18	54.5%	33
Male dominated	Miltary Industrial Complex	67	41.1%	163
	Housing and Community Services	95	39.1%	243
	Chemical Industry	14	38.9%	36
	Civil Machine Construction	51	37.8%	135
	Agriculture	79	33.9%	233
	Transportation, Communication	186	33.6%	553
	Information Technology	9	32.1%	28
	Energy or Power Industry	41	31.3%	131
	Army, Internal Security	90	30.1%	299
	Other Heavy Industry	60	28.7%	209
	Oil and Gas Industry	52	23.5%	221
	Wood, Timber, Forestry	7	21.2%	33
	Construction	73	18.7%	391
	Total	3303	54.3%	6089

The Neuman and Weiss model provides an estimation of the depreciation rate for human capital, but by itself is unable to identify how much of that depreciation is external or internal. External depreciation is due to obsolescence (as new technologies make skills redundant) and internal depreciation is due to factors related to the individual. The previous section reported the finding that depreciation for female workers first exceeded and then was exceeded by depreciation for male workers. Examining differences in depreciation rate by the segregation classfication helps identify between internal and external depreciation based on a conjecture. The conjecture is that external depreciation would have a greater affect by industry sector, as technological change would propagate more rapidly through a sector rather than through occupations, which are dispersed across sectors.

Table 3.3 depicts average rates of human capital loss due to experience and education by the female- and male-dominated industrial sectors and occupations. Industry or sector related differences does show difference in the depreciation rate, with depreciation rate being higher for male dominated industrial sectors. These are engineering and technology oriented sectors, compared to administration, services, and education which are the

Table 3.2: Occupations by Strength of Female Proportion, RLMS 2018

	Occupation	N fem	% fem	N total
1	Personal Care Workers	97	97.0%	100
2	Cleaners and Helpers	163	95.9%	170
3	Food Preparation Assistants	21	95.5%	22
4	Teaching Professionals	370	93.4%	396
5	General and Keyboard Clerks	71	93.4%	76
6	Other Clerical Support Workers	25	92.6%	27
7	Business and Administration Professionals	97	91.5%	106
8	Health Associate Professionals	192	91.4%	210
9	Health Professionals	79	87.8%	90
10	Sales Workers	350	86.6%	404
11	Customer Services Clerks	67	85.9%	78
12	Legal, Social and Cultural Professionals	169	80.5%	210
13	Business and Administration Associate Professionals	517	77.4%	668
14	Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers	51	77.3%	66
15	Administrative and Commercial Managers	25	71.4%	35
16	Personal Services Workers	172	70.5%	244
17	Hospitality, Retail and Other Services Managers	38	69.1%	55
18	Legal, Social, Cultural and Related Associate Professionals	69	65.7%	105
19	Numerical and Material Recording Clerks	100	63.3%	158
20	Production and Specialized Services Managers	139	46.0%	302
21	Handicraft and Printing Workers	9	45.0%	20
22	Science and Engineering Professionals	101	42.8%	236
23	Stationary Plant and Machine Operators	72	39.6%	182
24	Agricultural, Forestry and Fishery Labourers	11	39.3%	28
25	Refuse Workers and Other Elementary Workers	30	39.0%	77
26	Miscellaneous non-ISCO	9	36.0%	25
27	Science and Engineering Associate Professionals	120	34.9%	344
28	Chief Executives, Senior Officials and Legislators	7	29.2%	24
29	Information and Communications Technology Professionals	15	21.7%	69
30	Labourers in Mining, Construction, Manufacturing and Transport	24	20.9%	115
31	Assemblers	11	18.3%	60
32	Building and Related Trades Workers (excluding Electricians)	23	11.1%	207
33	Protective Services Workers	23	10.7%	215
34	Electrical and Electronic Trades Workers	16	9.9%	162
35	Drivers and Mobile Plant Operators	23	4.1%	558
36	Metal, Machinery and Related Trades Workers	6	2.2%	267

female dominated sectors. The depreciation does not appear to vary across occupational groupings - male dominated and female dominated occupation groupings have similar depreciation rates. These findings need to be treated as preliminary findings as they are only point estimates of depreciation, evaluated at mean values.

Table 3.3: Average Human Capital Depreciation Rates (DR) by Female- and Male-dominated Industries and Occupations, RLMS 2018

Statistic	Ind_F	Ind_M	occfemale	occmale
1 Experience, mean	23.45	22.97	21.67	23.48
2 Education, mean	14.06	13.01	13.67	12.67
3 DR Experience, %	0.89	1.82	1.55	1.40
4 DR Education, %	0.00	0.00	0.00	0.00
5 DR Human Capital, %	0.89	1.82	1.55	1.40

3.2 Depreciation and Occupational Routineness

In addition to the examination of human capital depreciation rates in gender-dominated industries and occupations, we explore differences in depreciation between groups generated by using an array of routine and non-routine task content metrics for jobs. This is important in light of discussion about computers and robots taking over routine oriented jobs. In this analysis, we rely on a recent literature of job classification based on task intensity measures Mihaylov and Tijdens (2019). These measures are based on the textual analysis of description of jobs in the ISCO 08 classification. Each job lists a detailed set of activities or tasks performed as part of the job, and these activities are rated according to whether they are vulnerable to automation in which case they are classified as Routine (R), otherwise they are Non-Routine (NR). Tasks are also classified depending on their Cognitive (C) or Manual (M) requirements; Cognitive taks are further classified as mainly Analytic (A) or Interactive (I). The results is a five-fold classification of tasks, which is subsequently used to develop a set of measures depending on the incidence of these tasks in the job description.

For purpose of this analyis, we use two of these measures. Routine Task Intensity measure (RTI) denotes a score difference between the summed routine task indices and the summed non-routine task indices: $(RC + RM) - (NRA + NRI + NRM)$ - it is a net measure of job routineness or vulnerability to automation. We also use a gross measure that brings together the non-routine task indices: $NRA + NRI + NRM$. Using the k-means clustering technique for the metrics described, we created two respective categorical variables (drti and dnraim) with categories capturing *high, medium,* and *low* manifestations of the features.

Table 3.4 shows the results of comparing depreciation rates between individuals whose jobs invoke routine or non-routine tasks at a high, medium, or low level. The findings suggest that depreciation explained by experience does not differ substantially between people with jobs with varying routine task intensity. The same outcome also applies to workers varying in the degree of non-routine content at their jobs. As with the findings regarding gender, these should be regarded as preliminary findings subject to further analysis. However, it does appear that the automation aspect of technological change may not be affecting the rate of depreciation of skills - both routine and non-routine intensive jobs undergo depreciation, though it is possibly that the underlying causal factors may be different.

Table 3.4: Average Human Capital Depreciation Rates (DR) by Routineness Classification, RLMS 2018

Statistic	High	Low	Medium	High	Low	Medium
	Net Routine Task Intensity			Gross Non-Routiness Measure		
1 Measure	drti	drti	drti	dnraim	dnraim	dnraim
2 Experience, mean	21.44	22.79	22.76	22.94	22.22	22.05
3 Education, mean	12.86	13.67	12.8	13.66	12.76	13.02
4 DR Experience, %	1.8	1.5	1.64	1.62	1.73	1.48
5 DR Education, %	0	0	0	0	0	0
6 DR Human Capital, %	1.8	1.5	1.64	1.62	1.73	1.48

4 Regional Returns to Education in the Russian Federation: Role of access to Vocational and Higher Education

4.1 Data

To estimate returns to education in Russian regions, we use the most recent (2018) round of the Statistical Survey of Income and Participation in Social Programs, collected by Rosstat. The primary purpose of the Rosstat survey was to obtain statistical information, reflecting the role of wages, income from self-employment, property income, pensions, and social benefits in ensuring the material well-being of families. The survey contains data on trends in income and poverty variation among households with different socio-economic status. There are also variables on people's participation in social programs, their pension and health insurance, material and social security of low-income families, and the impact of social policy measures on people's well-being. The sample selected for the empirical modeling is identical to the one used for the RLMS analysis: individuals aged 25-64 who are out of school and have positive labor market experience and income.

4.2 Methods

The classical Mincerian equation (described in the previous sections) is the main focus in the regional investigation of returns to education in Russia: in this section we look at how these returns vary across regions. Additionally, we explore the determinants of the established variation through a random effects regression analysis. The equations of interest are as follows:

First level:

$$Log(Wage)_{ij} = b_{0j} + b_{1j} \cdot Educ + b_{2j} \cdot Exp + b_{3j} \cdot Exp^2 + b_{4j} \cdot Gender + \epsilon_{ij} \tag{4.1}$$

Second Level:

$$b_{0j} = \gamma_{00} + \gamma_{0n} \cdot Z + u_{00}; \quad b_{1j} = \gamma_{10} + \gamma_{1n} \cdot Z + u_{10}; \quad b_{ij} = \gamma_{i0} \quad for \quad i \neq 0 \tag{4.2}$$

where an individual i is nested withing a region j, $Log(Wage)$ is a logarithm of monthly wage, $Educ$ stands for highest attained level of education, Exp and Exp^2 reflect the years of working experience and its quadratic term respectively, $Gender$ is a dummy variable for gender, Z is an $n \times i$ matrix of regional characteristics, ϵ and u_{00}, u_{10} are the first- and second-level errors respectively.

The random effects models were estimated using restricted maximum likelihood (REML). Individual Wald tests and likelihood ratio tests were exploited to evaluate the significance of fixed and random effects, respectively. Weights were used in the modeling to ensure the representativeness of the sample across Russian regions (the weighting variable was divided by 1000 to allow the convergence of the multilevel models).

Left Hand Side (LHS) variable

Similar to the previous analyses, the outcome to be investigated is the logarithm of monthly monetary remuneration before income tax payment at the main place of work.

Right Hand Side (RHS) variables

Education, experience, and gender are the first-level variables. Education is included in the random effects models as the focus of interest with a set of regional level variables - equation 4.2.

The random effects model seeks to estimate the magnitude of influence of regional level educational quantity and educational quality measures to explain the variation in returns to education across Russian regions. To measure educational quanity or access, we use the number of students enrolled in vocational education per 10,000 residents and the number of students enrolled in higher education per 10,000 residents. As a measure of educational quality, we use standard deviations from the national mean of the Russian school-leaving and university entrance examination, the EGE. We also add control variables regarding economic development and the labor market - these are respectively the gross regional product, the level of urbanization, the regional unemployment level and the the share of employment in jobs related to natural resource exploitation. Table 4.1 demonstrates the descriptive statistics by region.

Table 4.1: Descriptive Statistics for the Variables by Regions in Russia, Rosstat 2018

		Wage		Experience		Education, %			Gender, %	
Regions	**N**	**mean**	**sd**	**mean**	**sd**	**SE**	**VE**	**HE**	**Males**	**Females**
Altayskiy Kray	4646	22127.6	11952.2	23.6	11.0	17.456	54.50	28.05	48.90	51.10
Amurskaya Oblast	2557	33441.2	17409.0	23.2	11.2	16.347	50.65	33.01	49.59	50.41
Arkhangelskaya Oblast	3183	33438.1	16884.2	22.6	10.6	12.692	54.95	32.36	44.17	55.83
Astrakhanskaya Oblast	2836	26474.1	13737.6	23.0	11.3	13.646	55.08	31.28	50.99	49.01
Belgorodskaya Oblast	3692	26281.0	10811.9	23.8	11.1	12.351	54.47	33.18	49.76	50.24
Bryanskaya Oblast	3087	22482.3	9634.1	23.5	10.9	19.631	50.66	29.71	48.66	51.34
Chechenskaya Respublika	2010	27718.4	11793.2	18.7	10.6	25.721	26.37	47.91	65.37	34.63
Chelyabinskaya Oblast	6717	27990.8	14280.9	23.9	11.2	12.104	54.53	33.36	47.39	52.61
Chukotskiy Aok	1535	65574.1	32370.8	23.6	10.6	13.941	46.06	40.00	43.97	56.03
Chuvashskaya Respublika	3248	21453.7	12602.2	24.3	11.0	19.119	50.80	30.08	50.18	49.82
Evreyskaya AOb	1536	28532.1	17385.1	23.8	11.2	22.005	50.33	27.67	50.00	50.00
Irkutskaya Oblast	4686	29967.6	17443.1	22.3	11.2	17.520	47.06	35.42	47.57	52.43
Ivanovskaya Oblast	2876	24881.8	12496.8	23.3	10.9	20.341	49.90	29.76	47.77	52.23
Kabardino-Balkarskaya Res.	2006	23592.3	10766.2	21.7	11.6	21.137	40.53	38.33	52.04	47.96
Kaliningradskaya Oblast	2838	29749.2	15489.1	23.5	11.4	13.495	52.40	34.11	50.07	49.93
Kaluzhskaya Oblast	3155	29662.1	12879.5	24.1	11.2	13.312	52.11	34.58	47.92	52.08
Kamchatskaya Kray	2203	51160.5	29997.7	23.1	11.2	13.118	42.99	43.89	47.89	52.11
Karachayevo-Cherkessiya	1510	22900.6	12540.8	22.0	11.8	17.152	40.07	42.78	48.01	51.99
Kemerovskaya Oblast	5056	26287.0	13774.4	23.6	11.3	18.137	52.99	28.88	48.04	51.96
Khabarovskiy Kray	3731	42008.8	21837.8	22.3	11.2	11.900	44.33	43.77	46.15	53.85
Khanty-Mansiyskiy Aok	4335	50837.9	22261.7	22.8	10.5	13.564	46.78	39.65	49.60	50.40

Table 4.1: Descriptive Statistics for the Variables by Regions in Russia, Rosstat 2018

		Wage		Experience		Education, %			Gender, %	
Regions	**N**	**mean**	**sd**	**mean**	**sd**	**SE**	**VE**	**HE**	**Males**	**Females**
Kirovskaya Oblast	3284	22941.0	13674.6	25.1	11.2	20.128	55.33	24.54	47.69	52.31
Kostromskaya Oblast	2518	23993.1	12090.9	23.6	11.1	12.669	61.28	26.05	47.82	52.18
Krasnodarskiy Kray	8730	32563.7	17499.8	23.0	10.9	15.888	48.57	35.54	50.02	49.98
Krasnoyarskiy Kray	5540	33954.6	21199.2	23.0	11.0	21.588	48.05	30.36	49.64	50.36
Kurganskaya Oblast	2468	20896.9	11539.5	24.4	10.7	21.394	52.47	26.13	48.38	51.62
Kurskaya Oblast	2956	23622.6	11475.0	23.9	11.0	14.783	52.17	33.05	50.30	49.70
Leningradskaya Oblast	4506	32124.3	17227.4	24.2	11.5	7.723	54.77	37.51	46.03	53.97
Lipetskaya Oblast	2869	25037.8	10813.5	24.1	11.0	13.106	53.82	33.08	49.60	50.40
Magadanskaya Oblast	1841	51000.8	23729.4	24.1	11.4	18.523	43.02	38.46	43.24	56.76
Moscow	29921	66263.5	26437.9	20.8	10.8	4.953	32.18	62.86	47.06	52.94
Moskovskaya Oblast	13431	46725.1	20563.7	22.6	11.4	10.975	39.13	49.89	47.51	52.49
Murmanskaya Oblast	3078	43992.5	28841.9	23.4	11.2	12.801	50.45	36.74	49.84	50.16
Nenetskiy Aok	1118	54467.3	23147.1	22.6	10.8	17.263	49.73	33.01	39.98	60.02
Nizhegorodskaya Oblast	6139	30912.9	13291.8	23.4	11.2	16.941	49.31	33.75	47.42	52.58
Novgorodskaya Oblast	2673	26856.0	12683.0	24.6	11.2	15.638	55.74	28.62	45.16	54.84
Novosibirskaya Oblast	5374	29229.9	14687.7	23.9	11.6	16.561	49.33	34.11	47.06	52.94
Omskaya Oblast	3978	25337.5	14613.1	23.6	10.9	22.197	51.31	26.50	51.11	48.89
Orenburgskaya Oblast	4190	24207.0	12519.9	23.3	11.0	15.131	53.68	31.19	51.29	48.71
Orlovskaya Oblast	2424	21901.2	10561.0	24.7	11.1	15.017	50.66	34.32	46.99	53.01
Penzenskaya Oblast	3103	23478.4	10982.9	24.2	11.0	20.722	51.40	27.88	51.02	48.98
Permskiy Krai	5290	29176.6	14449.4	23.4	11.0	13.894	58.32	27.79	48.17	51.83
Primorskiy Kray	4104	37839.9	18420.2	23.8	11.3	14.985	52.97	32.04	49.98	50.02
Pskovskaya Oblast	2382	23838.4	12015.3	25.0	11.0	17.632	55.33	27.04	48.11	51.89
Respublika Adygeya	2013	21350.3	10505.9	23.4	11.3	20.666	43.67	35.67	49.53	50.47
Respublika Altay	1381	20285.3	12029.5	23.0	10.6	23.027	45.26	31.72	43.08	56.92
Respublika Bashkortostan	7126	31100.8	15175.2	23.4	11.0	12.167	56.67	31.17	51.98	48.02
Respublika Buryatia	2469	29536.3	17237.4	22.1	10.6	17.173	45.61	37.22	48.12	51.88
Respublika Crimea	2895	19916.2	9743.9	22.8	11.0	21.244	43.90	34.85	52.99	47.01
Respublika Dagestan	3388	26377.3	11971.9	23.0	10.7	30.519	30.79	38.70	55.99	44.01
Respublika Ingushetiya	1207	23740.2	10168.5	18.2	9.6	10.025	18.89	71.09	61.14	38.86
Respublika Kalmykiya	1751	18568.8	11749.1	23.6	11.4	15.762	40.89	43.35	46.43	53.57
Respublika Karelia	2164	28510.2	16639.5	23.7	10.8	17.144	55.45	27.40	47.00	53.00
Respublika Khakasiya	2064	27288.1	16613.3	23.3	11.1	22.045	51.11	26.84	50.97	49.03
Respublika Komi	2972	35891.6	21554.4	23.8	11.0	16.689	53.47	29.85	46.67	53.33
Respublika Mariy El	2486	21133.1	11941.6	24.1	11.2	18.785	52.98	28.24	47.87	52.13
Respublika Mordovia	2236	21221.0	10837.3	23.1	11.2	15.519	49.11	35.38	48.35	51.65
Respublika Saha (Yakutia)	3243	45763.1	25001.6	23.2	11.3	18.440	45.76	35.80	46.69	53.31
Respublika Severnaya Osetiya	2114	22993.1	12762.5	21.8	11.3	12.677	40.92	46.40	48.91	51.09
Respublika Tatarstan	7212	30327.9	12928.8	23.5	11.1	18.691	48.64	32.67	51.48	48.52
Respublika Tyva	1704	23421.9	16851.3	21.4	10.0	19.777	44.78	35.45	40.43	59.57
Rostovskaya Oblast	6985	28287.2	12779.9	23.1	11.0	15.476	48.03	36.49	50.68	49.32
Ryazanskaya Oblast	2609	25889.2	11760.9	24.7	11.1	12.457	59.37	28.17	49.18	50.82
Saint-Petersburg	11352	48520.8	23771.0	22.8	11.4	5.259	38.15	56.59	46.04	53.96
Sakhalinskaya Oblast	2258	50325.1	25563.0	23.6	11.2	17.493	48.23	34.28	46.94	53.06
Samarskaya Oblast	6275	32584.4	15015.6	23.8	11.1	11.331	47.87	40.80	47.71	52.29
Saratovskaya Oblast	4572	23698.6	12322.4	23.7	10.8	14.961	50.22	34.82	50.42	49.58
Sevastopol	1489	24811.3	13498.9	22.4	11.2	9.671	44.93	45.40	53.32	46.68
Smolenskaya Oblast	2726	25517.8	12104.9	24.6	11.3	14.380	52.31	33.31	46.04	53.96
Stavropolskiy Kray	4945	25263.6	12696.7	22.6	11.3	16.946	43.80	39.25	47.48	52.52
Sverdlovskaya Oblast	7712	35983.2	15242.7	23.6	11.3	16.779	54.94	28.28	48.59	51.41
Tambovskaya Oblast	2781	22698.6	10440.1	24.1	11.0	16.397	53.54	30.06	50.67	49.33
Tomskaya Oblast	3074	29580.6	16745.7	22.1	11.1	13.500	47.56	38.94	46.78	53.22
Tulskaya Oblast	3516	27687.4	11814.7	24.3	11.3	17.491	54.69	27.82	48.98	51.02
Tverskaya Oblast	3157	26310.0	15025.1	25.5	11.1	14.824	56.57	28.60	44.73	55.27
Tyumenskaya Oblast	3095	31441.2	17278.6	22.7	11.2	16.123	52.89	30.99	50.05	49.95
Udmurtskaya Respublika	4073	24044.6	11540.9	23.9	11.3	20.108	51.04	28.85	46.99	53.01
Ul'yanovskaya Oblast	3109	23215.3	10596.4	24.8	10.9	19.170	53.84	26.99	50.37	49.63
Vladimirskaya Oblast	3502	25001.4	12605.8	24.5	11.4	19.503	50.77	29.73	46.49	53.51
Volgogradskaya Oblast	4836	24459.0	12915.8	23.2	11.0	15.881	50.91	33.21	49.69	50.31
Vologodskaya Oblast	2965	28248.9	16693.8	23.9	11.2	17.302	57.47	25.23	49.61	50.39

Table 4.1: Descriptive Statistics for the Variables by Regions in Russia, Rosstat 2018

		Wage		Experience		Education, %			Gender, %	
Regions	**N**	**mean**	**sd**	**mean**	**sd**	**SE**	**VE**	**HE**	**Males**	**Females**
Voronezhskaya Oblast	4348	26261.9	11813.9	23.6	11.5	22.700	43.38	33.92	48.37	51.63
Yamalo-Nenetskiy Aok	3164	69356.7	28075.6	21.0	10.4	10.683	40.27	49.05	48.74	51.26
Yaroslavskaya Oblast	3361	30261.4	14682.8	24.1	11.4	16.215	53.73	30.05	47.01	52.99
Zabaykalskiy Kray	3017	28336.6	16350.4	23.0	10.6	24.561	47.40	28.04	47.07	52.93

4.3 Estimation Results of Regional Analysis

First, simple linear regression models were fitted to the observations in each region, and 95% confidence intervals for the education variable coefficients were returned to examine the overall pattern of regional diversity in education payoffs. A visual inspection of Figure 4.1 is illustrative of the fact that Russian regions are rather heterogeneous in terms of premiums to education. Following the basic Mincerian equation, we present the results of the multilevel regression.

A two-level model without covariates was initially specified and indicated that the Intra-class Correlation (ICC) was equal to 16%, i.e., 16% of the variation in wage outcome was between regions. This is a high enough level to justify the estimation of a random effects model with covariates. Nested models comparison showed that there is a statistically significant regional variation in the effect of education on people's earnings $\left(-2 \triangle LL(1) = 413.54, p < .001\right)$.

Next, we examined the possible causes of this variation by adding the second-level independent variables and their interactions with education. The investigation revealed that none of the second-level characteristics are capable of changing the association between education and the amount of money Russians earn, except for *the coverage by vocational education*. Substantively, it means that growth in the number of students covered by vocational programs leads to higher schooling premiums concerning both vocational and university education. As for the estimates obtained, sufficiently high vocational education coverage degree (when its standardized version is 1) corresponds to the average return rate of 30.6%; medium vocational education coverage degree (when its standardized version is 0) corresponds to the average return rate of 35.8%; low vocational education coverage degree (when its standardized version is -1) corresponds to the average return rate of 25.5%. The interpretation of such a finding can imply that this quantity-related dimension of vocational education has the potential to serve as an instrument of boosting financial payoffs from post-secondary education in Russian regions.

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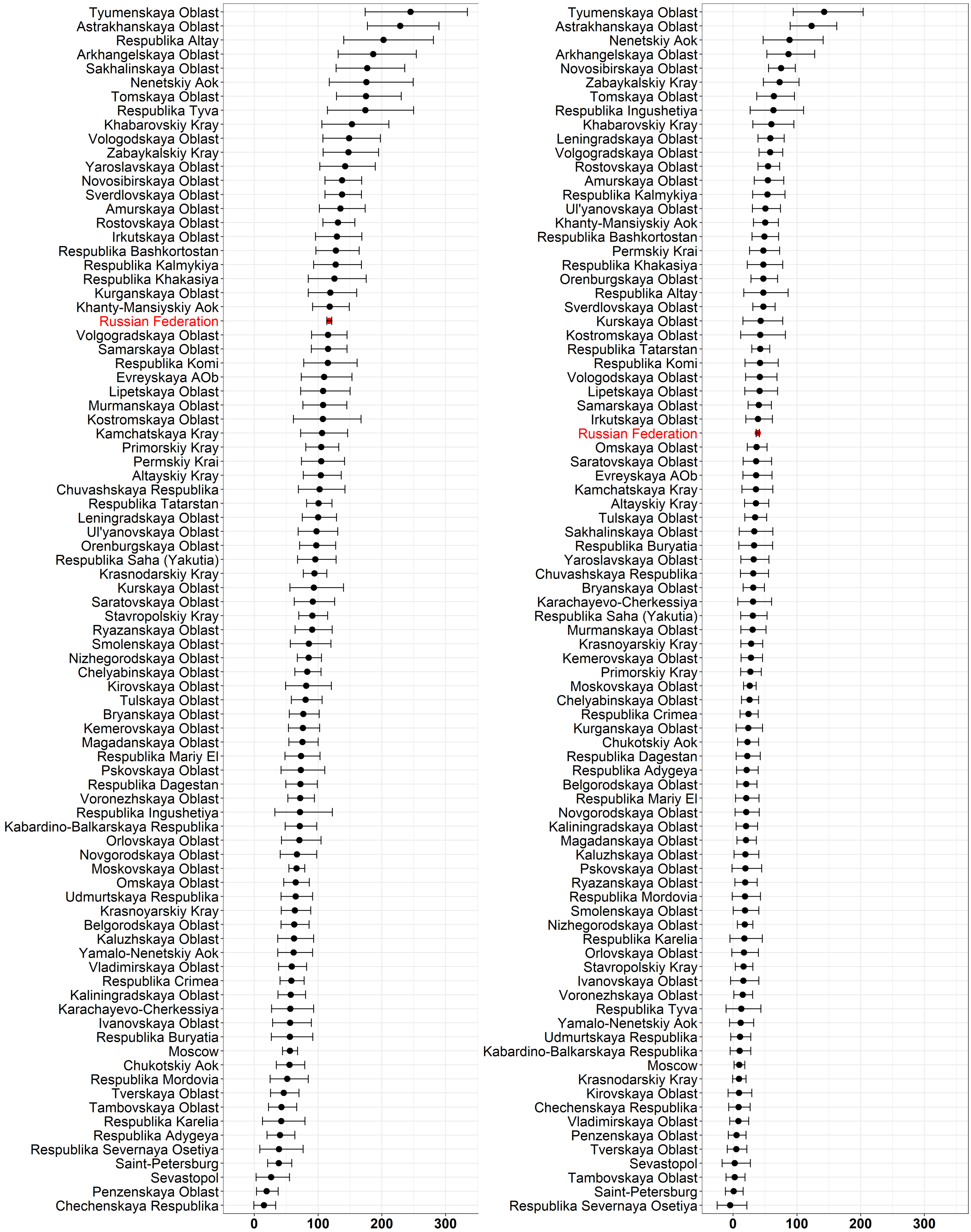

(a) Higher Education

(b) Vocational Education

Figure 4.1: Rates of Returns (Percentages) to Higher and Vocational Education in Russian Regions, Rosstat 2018

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Appendix

Table A1: Results of Estimating Human Capital Depreciation for the Female sample, RLMS

	1994	**1998**	**2003**	**2006**	**2012**	**2018**
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	9.725***	3.786***	5.464***	6.946***	8.133***	8.767***
	(0.381)	(0.322)	(0.301)	(0.247)	(0.186)	(0.242)
Educ, years (S)	0.122***	0.153***	0.158***	0.118***	0.087***	0.066***
	(0.025)	(0.022)	(0.020)	(0.016)	(0.012)	(0.015)
Educ X Exper (TS)	−0.002*	−0.002***	−0.002**	−0.0002	−0.0001	0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)
Exper (T)	0.074***	0.080***	0.055***	0.013	0.020**	0.020*
	(0.019)	(0.016)	(0.015)	(0.013)	(0.010)	(0.011)
Exper squared (T^2)	−0.001***	−0.001***	−0.001***	−0.0003**	−0.0005***	−0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	1,645	1,667	2,093	2,630	4,057	3,312
R^2	0.051	0.089	0.110	0.139	0.104	0.092
Adjusted R^2	0.049	0.087	0.108	0.138	0.103	0.091
Residual Std. Error	0.853	0.728	0.731	0.664	0.641	0.597
F Statistic	22.179***	40.520***	64.342***	106.385***	117.366***	83.993***

Note: *p<0.1; **p<0.05; ***p<0.01

Table A2: Results of Estimating Human Capital Depreciation for the Male sample, RLMS

	1994	**1998**	**2003**	**2006**	**2012**	**2018**
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	10.357***	5.029***	7.334***	8.067***	8.771***	9.094***
	(0.433)	(0.360)	(0.282)	(0.243)	(0.157)	(0.185)
Educ, years (S)	0.136***	0.123***	0.080***	0.077***	0.077***	0.077***
	(0.028)	(0.024)	(0.019)	(0.016)	(0.010)	(0.012)
Educ X Exper (TS)	−0.002*	−0.001	0.0004	−0.0003	−0.0004	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)
Exper (T)	0.054**	0.032*	0.002	0.007	0.035***	0.037***
	(0.023)	(0.017)	(0.014)	(0.013)	(0.009)	(0.010)
Exper squared (T^2)	−0.001***	−0.0004**	−0.0003*	−0.0003*	−0.001***	−0.001***
	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	1,392	1,433	1,763	2,170	3,360	2,800
R^2	0.057	0.070	0.078	0.074	0.153	0.110
Adjusted R^2	0.054	0.067	0.076	0.072	0.152	0.108
Residual Std. Error	0.951	0.803	0.754	0.688	0.598	0.570
F Statistic	20.989***	26.879***	37.362***	43.281***	151.868***	86.125***

Note: *p<0.1; **p<0.05; ***p<0.01

Table A3: Results of Multilevel Modeling with Coverage by Vocational Education, Rosstat 2018

	Null model	Mincerian	Random Slope	Cross-Level Interaction
	(1)	(2)	(3)	(4)
Constant	10.178***	10.032***	10.056***	10.065***
	(0.034)	(0.034)	(0.036)	(0.036)
Vocational		0.283***	0.279***	0.267***
		(0.009)	(0.021)	(0.021)
Higher		0.638***	0.641***	0.622***
		(0.009)	(0.025)	(0.025)
Coverage VE X Vocational				0.050**
				(0.025)
Coverage VE X Higher				0.083***
				(0.030)
Experience		−0.026***	−0.027***	−0.027***
		(0.002)	(0.002)	(0.002)
Experience squared		−0.065***	−0.065***	−0.065***
		(0.002)	(0.002)	(0.002)
Females		−0.403***	−0.404***	−0.404***
		(0.005)	(0.005)	(0.005)
Coverage VE			−0.101***	−0.142***
			(0.039)	(0.043)
Variance of Intecept	0.09	0.08	0.09	0.09
Variance of Vocational			0.02	0.02
Variance of Higher			0.04	0.04
Residual Deviance	0.45	0.35	0.34	0.34
Observations	49,187	49,187	49,187	49,187
Log Likelihood	−59,755.060	−53,289.500	−53,094.620	−53,096.640
Akaike Inf. Crit.	119,516.100	106,595.000	106,217.200	106,225.300
Bayesian Inf. Crit.	119,542.500	106,665.400	106,340.500	106,366.100
Note:				*p<0.1; **p<0.05; ***p<0.01