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Returns to Education in the Russian Federation: Does depreciation explain some recent trends?

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Data and Code
Thanks are due to the Higher School of Economics, Moscow for making the Russian Longitudinal Monitoring Study (RLMS) Household data readily available for reseachers around the world. 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. The code used for this paper is made freely available for all researchers at `https://bitbucket.org/zagamog/edreru/src/master/`

This paper explores the topic of depreciation of human capital as a possible explanation for observed trends in the returns to education in the Russian Federation. Estimates of depreciation are presented for various sample groups. Depreciation first decreased and then increased in the period 1994-2018. Post education investment in human capital is found to be higher amongst university educated workers.

KEYWORDS
Returns to Education, Depreciation, Gender segregation, Automation, *JEL Codes: I26, I28, J16, J29*

1 | 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

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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?

1.1 | 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 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 1.1 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 1.1a 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.

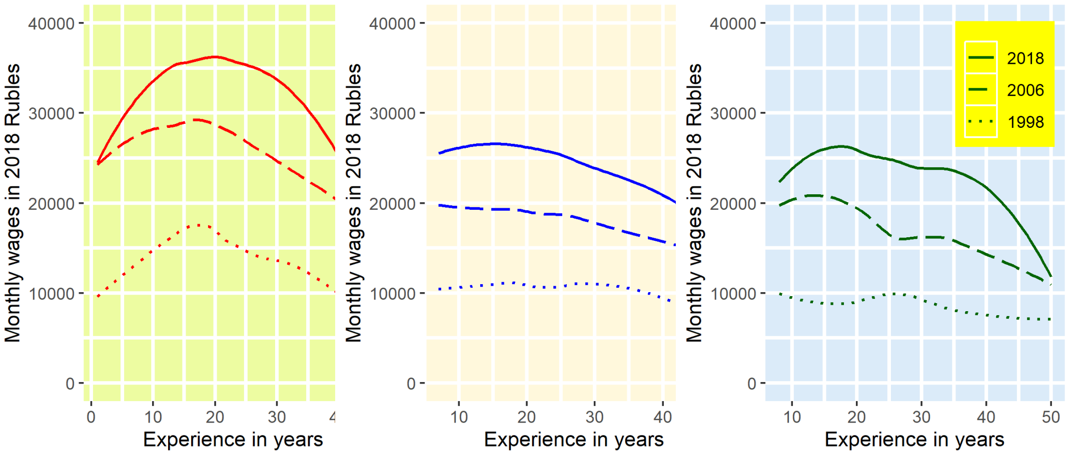
Putting the curves together by year (Figure 1.2) suggests that the premium for university education over the other two levels does narrow at higher levels of experience. In the figure, to accomodate the relatively lower wage levels of 1998, the leftmost panel (Figure 1.2a) is slightly compressed compared 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).

1.2 | 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:

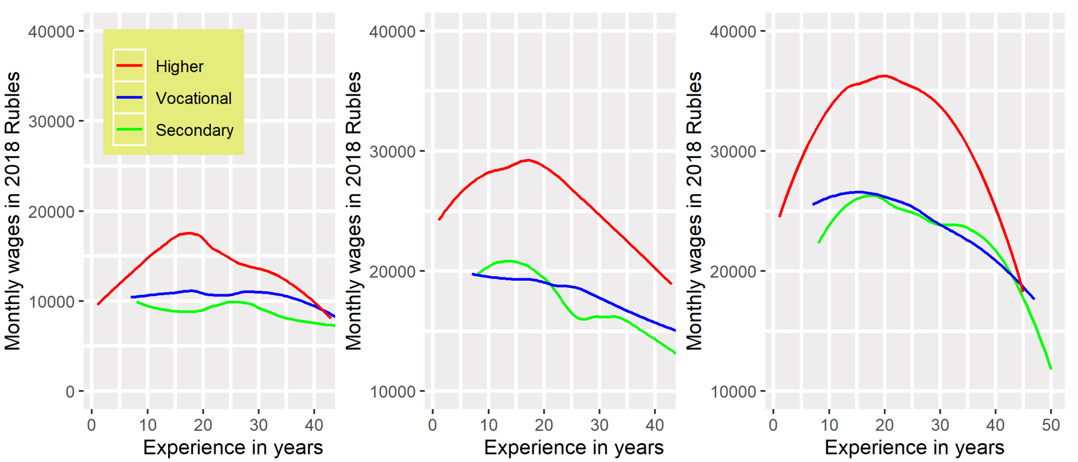
$$logW_T = \alpha + \beta_1 KS_T + \beta_2 KE_T \tag{1}$$

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



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

FIGURE 1.1 Neuman-Weiss vintage effects by education level from RLMS Rounds 1998, 2006 and 2018



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

FIGURE 1.2 Neuman-Weiss vintage effects by Year from RLMS Rounds 1998, 2006 and 2018 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

$$KS_T = S + hTS \tag{2}$$

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.

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

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

$$KE_T = T + \gamma \cdot \{T - 1 + T - 2 + T - 3 + \ldots + 1\} = T + \gamma \cdot \frac{T^2}{2} \tag{4}$$

Substituting equations 2 and 4 into equation 1, we get

$$logW = \alpha + \beta_1 S + \beta_1 hTS + \beta_2 T + \frac{\beta_2\gamma}{2}T^2 = \alpha + \beta_1 S + \pi_1 TS + \beta_2 T + \pi_2 T^2 \tag{5}$$

where $\pi_1 = \beta_1 h$ and $\pi_2 = \frac{\beta_2\gamma}{2}$. From 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 $2\pi_2 T$.

1.2.1 | Estimation Results

In the first working paper of this series, we presented an apparent inverted-U shaped trend in the returns to education in the Russian Federation between 1994 and 2018 (Patrinos et al. 2020). In this paper exploring depreciation, we analyze separately six years that represent the ends (1994 and 2018), the diffused peak (2003 and 2006), and halfway points to the ends (1998 and 2012) of that inverted-U shape. Table 1.1 shows OLS estimation results of equation 5 run on the whole sample of the RLMS observations. The idea is to examine the role played by changes in depreciation to explain the observed pattern of variation in the rates of return over the time period.

Using the coefficient estimates derived from Table 1.1, 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 1.2 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.

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.

TABLE 1.1 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

TABLE 1.2 Average Depreciation Rate by Years

	Statistic	1994	1998	2003	2006	2012	2018
Panel A: Whole Sample							
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

1.3 | 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:

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

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:

$$E_t = W \cdot \exp\left(\beta_K K_t + \beta_Z Z_t\right) \tag{7}$$

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:

$$K_t = K_{t-1} - \delta \cdot K_{t-1} + \Delta K_t = 1 - \delta \cdot K_{t-1} + \Delta K_t \tag{8}$$

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:

$$K_t = 1 - \delta^t \cdot K_S + \sum_{j=S^*}^{t-1} 1 - \delta^j \cdot \Delta K_{t-j} \tag{9}$$

Taking the logarithms of the expression 7 and substituting K_t by the equation 9 leads to:

$$\ln E_t = \ln W + \beta_K \cdot \left\{ 1 - \delta^t \cdot K_S + \sum_{j=S^*}^{t-1} 1 - \delta^j \cdot \Delta K_{t-j} \right\} + \beta_Z Z_t \tag{10}$$

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:

$$\begin{aligned} Y_t &= \left(1 - s_t\right) \cdot E_t \\ \ln Y_t &= \ln\left(1 - s_t\right) + \ln E_t \end{aligned} \tag{11}$$

Combining 10 and 11 results in:

$$\ln Y_t = \ln W + \beta_K \cdot \left\{ 1 - \delta^t \cdot K_S + \sum_{j=S^*}^{t-1} 1 - \delta^j \cdot \Delta K_{t-j} \right\} + \beta_Z Z_t + \ln\left(1 - s_t\right) \tag{12}$$

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:

$$K_S = S \tag{13}$$

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

$$\Delta K_t = s_t = \begin{cases} 0 & \text{if } t < 6 \\ 1 & \text{if } 6 \leq t < S^\star \\ \alpha \cdot \left(1 - \frac{X_t}{L}\right) & \text{if } S^* \leq t \leq T \end{cases} \tag{14}$$

Using 8 and 11 to express K_S as a sum of the human capital quantities produced during schooling, the result is:

$$K_S \overset{3}{=} \overset{S^*}{\underset{j=0}{}} 1 - \delta^j \cdot \Delta K_{S^*-j} \overset{9}{=} \overset{S^*}{\underset{j=6}{}} 1 - \delta^j \tag{15}$$

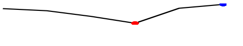
Substituting 13 and 14 into 12, adding an error term and an individual subscript i provides the equation that can be estimated using non-linear least squares (NLS):

$$\ln Y_{it} = \ln W + \beta_K \cdot \left\{ 1 - \delta^{X_{it}} \cdot S_i + \alpha \cdot \frac{1 - 1 - \delta^{X_{it}}}{\delta} \cdot \right. \\ \left. \left(1 + \frac{1-\delta}{\delta \cdot L_i}\right) - \frac{\alpha \cdot X_{it}}{\delta \cdot L_i} \right\} + \ln \left\{ 1 - \left(\alpha - \frac{\alpha}{L_i} \cdot X_{it} \right) \right\} + \beta_Z \cdot Z_{it} + u_{it} \tag{16}$$

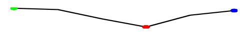
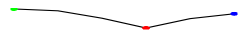
where t shows a time period, $\ln Y$ is a logarithm of the observed earnings, $\ln W$ is a logarithm of a return per certain period on a unit of earnings capacity, β_K is the effect of the human capital stock on earnings, β_Z is the effect of other covariates in the model on earning, δ is the human capital 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 1.3 reports empirical findings for the estimation of the 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).

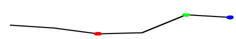
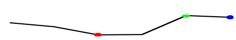
TABLE 1.3 Non-Linear Lest Squares estimated for range of years

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 1.3 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.

Adopting a strategy utilized by (Weber (2008)) and modifying the approach to fit the Russian context, Table 1.4 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 IV* - both α and δ vary across education levels.

Model I - the base model, has already been presented in Table 1.3 and is shown again as part of Table 1.4 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 1.4 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 1.4 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

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

2 | FURTHER EXPLORATION OF DEPRECIATION

2.1 | 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 $\pm$ 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 2.1 visualizes this procedure; Table 2.1 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 2.2 and Table 2.2).

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 2.3 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 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.

2.2 | 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

FIGURE 2.1 Distribution of Employment in RLMS 2018 by Industry and Gender

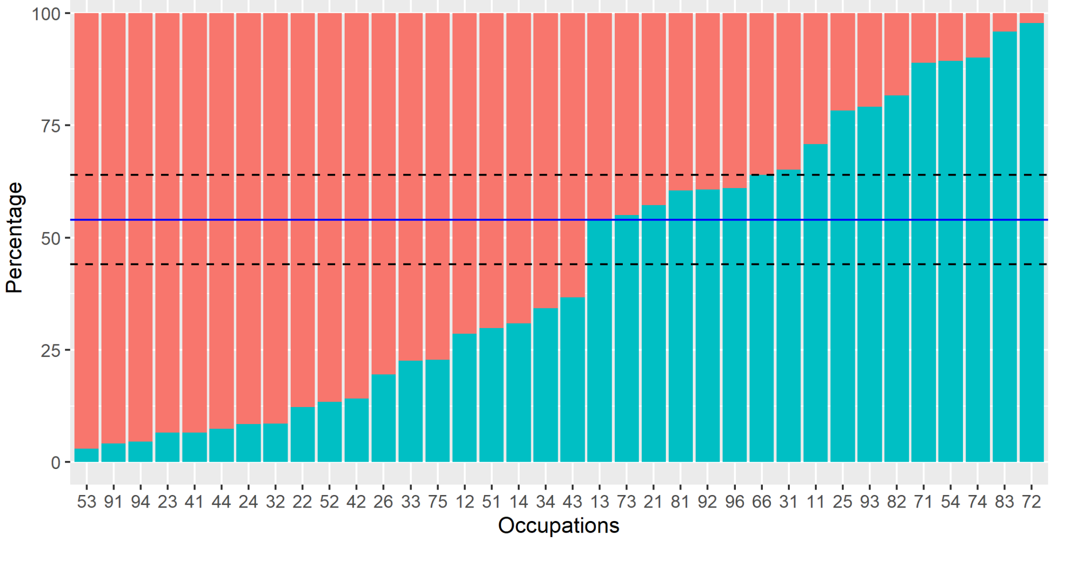


FIGURE 2.2 Distribution of Employment in RLMS 2018 by Occupation and Gender

TABLE 2.1 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

TABLE 2.2 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

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

TABLE 2.3 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

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 2.4 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 2.4 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

3 | SUMMARIZED FINDINGS

- **Depreciation of 2%** The topic of depreciation of human capital is important from the policy perspective because increasing the human capital can be made both by the creation of human capital as well as reducing the depreciation of human capital to the extent possible. In this paper per first presented an overview of the literature regarding depreciation of human capital and present estimates of depreciation in the Russian Federation. Depreciation appears to be around 2% per year in the most recent finding, with the depreciation mostly attributed to depreciation of human capital acquired with experience (Table1.2).

- **Depreciation declining then increasing** The pattern of the depreciation rate indicates a gentle decline followed by an increase in the period 1994-2018 (Table 1.2 and Table 1.3). This pattern is a reflection of the inverted-U shaped pattern of the rates of return to education. It is possible that depreciation may be an explanation for the observed tendency in the returns to education.
- **University educated individuals make more post-school investment too** In estimating rates of depreciation, we undertake an exploration of a related parameter that represents post-schooling investment in human capital. The data indicates that post-schooling investment for those with vocational education is indistinguishable from those with only secondary education. However, those with university education appear to be investing more in their working period (Table 1.4).
- **Males may be experiencing higher depreciation than females** The paper explored differences in depreciation rates across industrial and occupation groupings denoted by levels of gender segrgation. Depreciation rates appear to be higher in male dominated industrial sectors but gender related occupational groupings do not show this differential. The evidence suggests that external depreciation due to obsolecence may be a dominant component of the depreciation of human capital (Table 2.3).
- **Automation possibilities of jobs may not be related to depreciation** The paper used a relatively recent classification of jobs regarding the potential for automation depending on the routine or non-routine nature of tasks. It was hypothesized that routine intensive jobs which are more likely to be taken overy by computers may suffer from a higher depreciation rate, but the data do not reveal differences in depreciation rate by routine task intensity (Table 2.4).

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