Can Depreciation of Human Capital Explain Recent Trends in the Returns to Education?

Suhas D. Parandekar

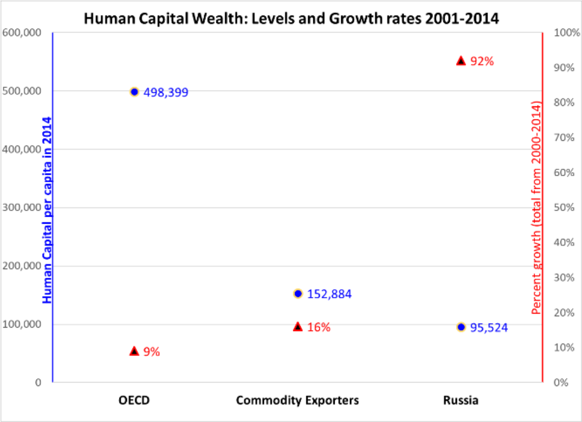
Returns to Education World Bank Workshop, 2020

Outline

1. Motivation
   - Stylized facts about Human Capital in the Russian Federation
2. Returns to Education in the Russian Federation
   - Data and Methods
   - Results
3. Depreciation of Human Capital in Russia
   - Analytical Treatment of Depreciation
   - Estimation Results
   - Arrazola's Non-Linear Least Squares Approach
   - Estimation Results
4. Further Exploration of Depreciation
   - Depreciation and the Gender Dimension
   - Depreciation and Occupational Routineness
5. Regional Returns to Education in the Russian Federation

Motivation

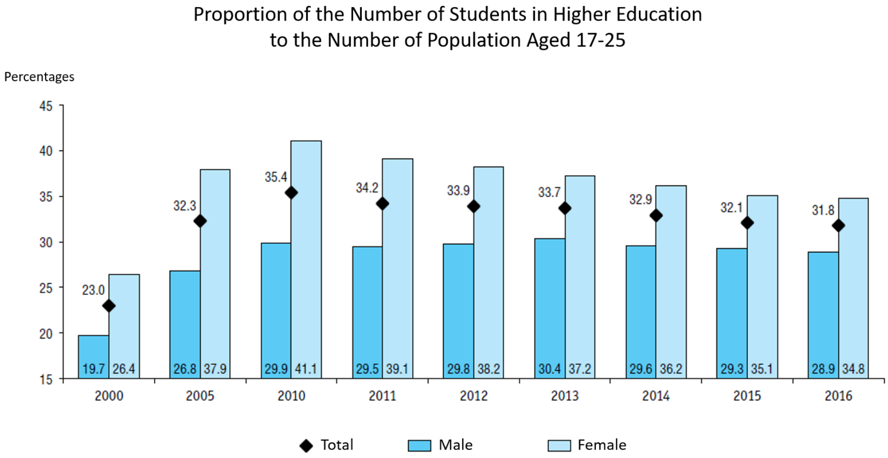
Human Capital Levels and Growth Rates: 2001-2014



- Per capita HC:
  - OECD - 500,000$
  - Russia - 95,000$
- With the 2000-2010 level of HC growth (4.7%), it would take ∼50 years to catch up with the OECD

Motivation

Peak in Enrollment in University Education (HSE Yearbook)

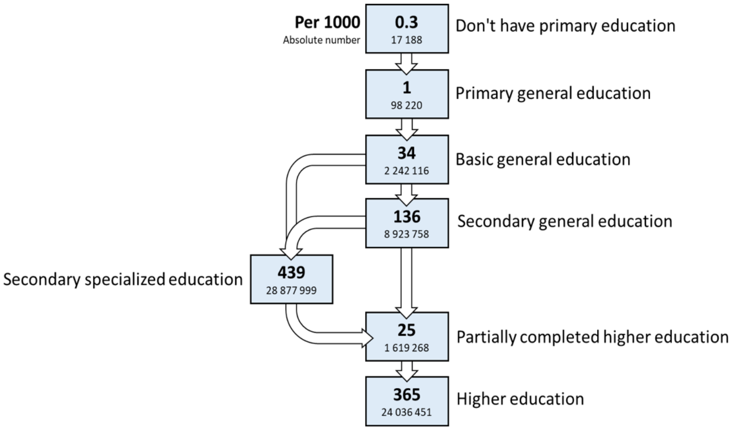


- Even as university enrollment had expanded rapidly since 2000, it appears to have peaked and then declined.

Motivation

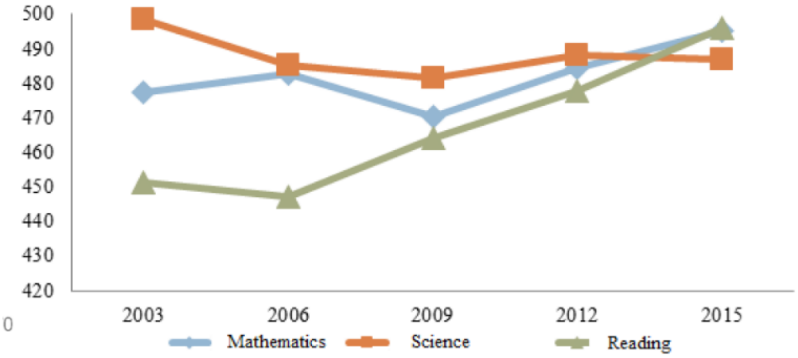
Labor Force Distribution by Educational Level (Rosstat)

Number of People in Russia Aged 25-54 by Achieved Level of Education
(per 1000 and an absolute number)



Motivation

PISA Mean Scores for Russian Federation (OECD/PISA)



- On cognitive attainment at Grade 9, Russian students are already at par with OECD students.

- **Data:** the Russian Longitudinal Monitoring Survey (RLMS), 1994-2018.
- **Sample:** working individuals aged 25-64 who are out of school and have positive labor market experience and income.
- **Methods:** Mincerian equations estimation:

$$\begin{aligned} Log(Wage) = b_0 + b_1 \cdot Education + b_2 \cdot Experience + \\ + b_3 \cdot Experience^2 + b_4 \cdot Gender + \epsilon \end{aligned} \quad (1)$$

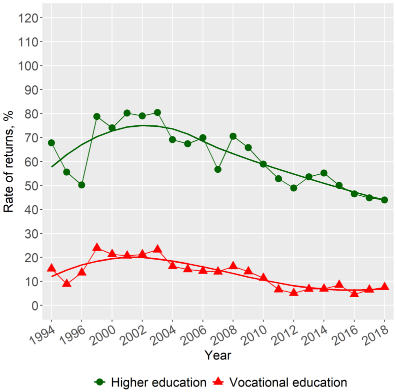
$$\begin{aligned} Log(Wage) = a_0 + a_1 \cdot D_{Vocational} + a_2 \cdot D_{Higher} + \\ + a_3 \cdot Experience + a_4 \cdot Experience^2 + a_5 \cdot Gender + \epsilon \end{aligned} \quad (2)$$

Results on Returns to Education in Russia

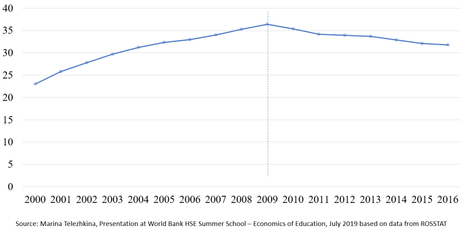
Rates of Overall and Gender-wise Returns to Education in 1994-2018

Results on Returns to Education in Russia

Co-movement of Vocational and Higher Education and Enrollment in Higher Education



(a) Rate of Returns to Education

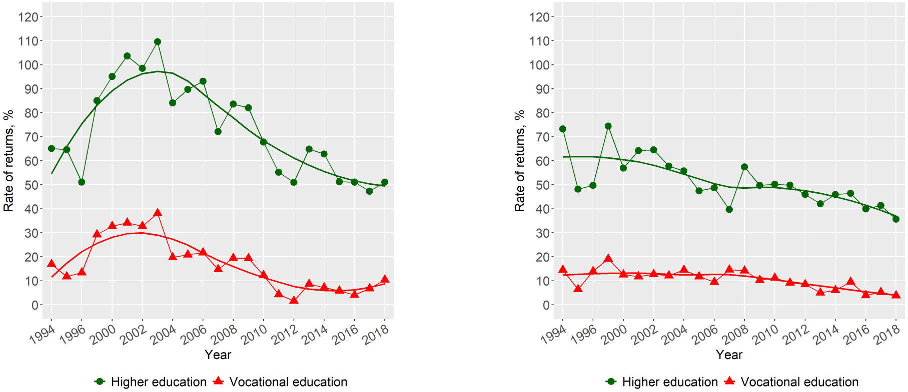


(b) Enrollment in Higher Education

- The graphs display downturn in returns reflected in enrollments, with the peak in enrollments coming about 10 years later.

Results on Returns to Education in Russia

Co-movement of Vocational Education and Higher Education by Gender



(a) Females

(b) Males

- Returns for males are almost flat.
- Returns for females show a *concave* pattern.

Two kinds of depreciation or *loss of productive potential of human capital* (Neuman and Weiss 1995):

- **External depreciation** (“obsolescence" or “vintage effect"): 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.
- **Internal depreciation:** due to deterioration of physical and mental abilities of an individual due to the progression of a person’s age.

Depreciation of Human Capital in Russia

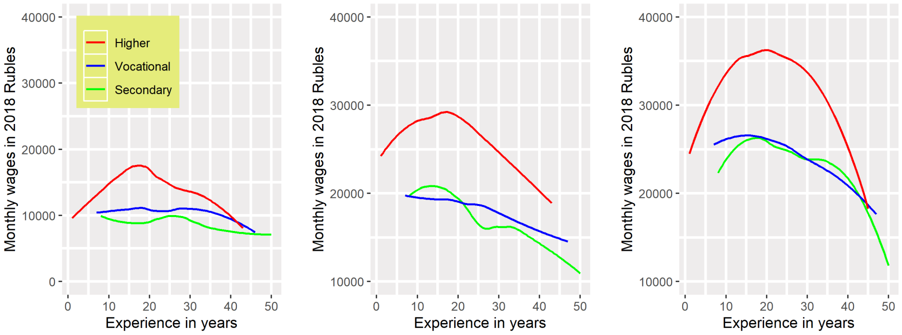
Neuman-Weiss Vintage Effects by Education Levels

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

- A clear concave downwards profile is only for Higher Education.
- The concave tendency is less pronounced for the other two levels of Vocational and Secondary education.

Depreciation of Human Capital in Russia

Neuman-Weiss Vintage Effects by Year



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

- The premium for university education over the other two levels does narrow at higher levels of experience.

- Murillo (2006) implemented a variation of the Neuman and Weiss (1995) model with a focus on empirical implementation to Spain.
- In a nutshell, the model can be expressed as follows:

$$log(W) = \alpha + \beta_1 S + \pi_1 TS + \beta_2 T + \pi_2 T^2 \tag{3}$$

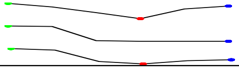
  where T is years of experience, S is years of schooling, α, β_1, β_1, π_1, π_2 are regression coefficients.
- The depreciation rate during T years applied to schooling can be computed as $\pi_1 S$ and the depreciation rate applied to experience as $2\pi_2 T$.

Depreciation of Human Capital in Russia

Average Depreciation Rate (DR) by Years

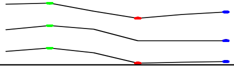
Panel A: Whole Sample

	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



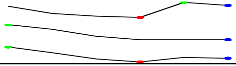
Panel B: Female Sample

	Statistic	1994	1998	2003	2006	2012	2018
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

	Statistic	1994	1998	2003	2006	2012	2018
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



- Arrazola et al. (2005) developed an alternative approach on the issue of human capital depreciation.
- The analytical solution culminates in the following equation to be estimated with Non-Linear Least Squares (the notations are taken from Weber (2008) and Weber (2011)):

$$\ln Y_{it} = \ln W + \beta_K \cdot \left\{ (1-\delta)^{X_{it}} \cdot S_i + \alpha \cdot \frac{1-(1-\delta)^{X_{it}}}{\delta} \cdot \left(1 + \frac{1-\delta}{\delta \cdot L_i}\right) - \frac{\alpha \cdot X_{it}}{\delta \cdot L_i} \right\} + \ln\left\{1 - \left(\alpha - \frac{\alpha}{L_i} \cdot X_{it}\right)\right\} + \beta_Z \cdot Z_{it} + u_{it} \tag{4}$$

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.

Depreciation of Human Capital in Russia

Results of Non-Linear Least Squares Estimation: Whole Sample

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	

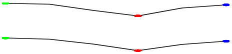
- The sparklines indicate a similar roughly U-shaped pattern for depreciation as reported for Murillo's estimations, with depreciation of human capital first declining and then increasing again.
- This supports the narrative that the observed increase and then decrease in returns to education in the Russian Federation may be explained through the effect of depreciation.

Depreciation of Human Capital in Russia

Results of Non-Linear Least Squares Estimation: by Gender

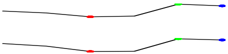
Panel B: Female Sample

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



- 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.

- 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*.
- Examining differences in depreciation rate by the **segregation classification** helps solve this problem 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.

Further Exploration of Depreciation

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

- DR is higher for **male-dominated industries** *(engineering and technology-oriented sectors)* compared to the female-dominated ones *(administration, services, and education)*.
- However, DR does not appear to vary across **occupational groupings**.

Further Exploration of Depreciation

Depreciation and Occupational Routineness

- In light of a discussion about computers and robots taking over routine-oriented jobs, we compare DR between **jobs and sectors with routine and non-routine task content** (Mihaylov and Tijdens 2019).
- These measures are based on the textual analysis of jobs description in the ISCO-08 classification.
- Using the *k-means clustering* for the routine and non-routine task metrics, we created two categorical variables with categories capturing *high*, *medium*, and *low* manifestations of the features.

Further Exploration of Depreciation

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

- DR 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.

Regional Returns to Education in the Russian Federation

- **Data:** the Statistical Survey of Income and Participation in Social Programs, 2018.
- **Sample:** identical to the one used for the RLMS analysis.
- **Methods:** Random effects regression analysis:

First level:

$$Log(Wage)_{ij} = b_{0j} + b_{1j} \cdot Education + \\ + b_{2j} \cdot Experience + b_{3j} \cdot Experience^2 + b_{4j} \cdot Gender + \epsilon_{ij} \quad (5)$$

Second Level:

$$b_{0j} = \gamma_{00} + \gamma_{0n} \cdot Regional\ characteristics + u_{00}; \\ b_{1j} = \gamma_{10} + \gamma_{1n} \cdot Regional\ characteristics + u_{10}; \\ b_{ij} = \gamma_{i0} \quad for \quad i \neq 0 \quad (6)$$

- **Results:** *Coverage by vocational education* serves as an instrument, boosting financial payoffs from post-secondary education in Russian regions.

Summary

- The Mincerian estimates show an increase in the returns in the first half of 1994-2018 period, followed by a gradual decline.
- Depreciation follows a **reverse trajectory**, decreasing and them increasing, which may explain part of the observed tendency for the returns to education.
- There is a positive association between **regional access to vocational education** and the rate of return to education.

References

Arrazola, María, et al. 2005. "132b. A Proposal to Estimate Human Capital Depreciation: Some Evidence for Spain". *Hacienda Publica Espanola–Revista de Economia Publica* 172 (1): 9–22.

Mihaylov, Emil, and Kea Gartje Tijdens. 2019. "152. Measuring the Routine and Non-Routine Task Content of 427 Four-Digit ISCO-08 Occupations". *Tinbergen Institute Discussion Paper* TI 2019-035/V.

Murillo, Ines P. 2006. "172. Returns to Education and Human Capital Depreciation in Spain". *Econstor Working Paper*.

Neuman, Shoshana, and Avi Weiss. 1995. "091. On the Effects of Schooling Vintage on Experience-Earnings Profiles: Theory and Evidence". *European economic review* 39 (5): 943–955.

Weber, Sylvain. 2011. "156. On the Impact of Education on Human Capital Depreciation, Wage Growth, and Tenure". PhD thesis, University of Geneva.

– . 2008. "173. Human Capital Depreciation and Education Level: Some Evidence for Switzerland". In *Annual Conference of the European Association of Labour Economists*. Amsterdam, The Nnetherlands.