ЭКОНОМИКА
ECONOMY
ЭКОНОМИКА

ECONOMIC RETURNS TO SKILLS IN KAZAKHSTAN IN THE CONTEXT OF INTERNATIONAL COMPARISONS

Saule KEMELBAYEVA* — *PhD in Economics, Associate Professor, International School of Economics, M. Narikbayev KAZGUU University, Nur-Sultan, Republic of Kazakhstan, s_kemelbayeva@kazguu.kz, ORCID: 0000-0002-7406-0589, Scopus ID: 57216337017*

Kaidar NURUMOV — *MA Political Science, Senior Analyst, JSC "Information Analytic Center", Nur-Sultan, Republic of Kazakhstan, kaidar.nurumov@iac.kz, ORCID: 0000-0002-1514-0095, Scopus ID: 57264987100*

Azat AITUAR — *PhD in Economics, Assistant Professor, International School of Economics, M. Narikbayev KAZGUU University, Nur-Sultan, Republic of Kazakhstan, a.aituar@kazguu.kz, ORCID: 0000-0002-7625-8783, Scopus ID: 57280245800*

Yerkezhan DYSENBEKOVA — *Master student in Economics, International School of Economics, M. Narikbayev KAZGUU University, Nur-Sultan, Republic of Kazakhstan, ye_dyussenbekova@kazguu.kz*

DOI: 10.52123/1994-2370-2022-625
UDC 33
CICSTI 06.52.01

Abstract. The study examines the economic returns to literacy, numeracy and problem-solving skills in adults in Kazakhstan with the OECD data. Unlike in other countries, the returns to skills are neither economically nor statistically significant. This finding, however, is fully driven by the public sector of the economy, while in the private sector the skills significantly improve one's earnings. The returns to formal education accounting for skills are comparable in public and private sectors. This likely causes the outflow of most productive workers to the private sector and question the efficiency of the public sector of the economy in Kazakhstan.
Keywords: returns to education, adult skills, functional literacy, Kazakhstan, public and private sector.
JEL codes: I26, J31, H32

Аңдатпа. Зерттеуде ЭЫДҰ деректерін пайдалана отырып, Қазақстандағы ересектердің сауаттылық, есеп және міндеттерді шешу дағдыларынан экономикалық қайтарымы қаралады. Басқа елдерден айырмашылығы, дағдылардың қайтарымы экономикалық жағынан да, статистикалық тұрғыдан да маңызды емес. Алайда, бұл тұжырым экономиканың мемлекеттік секторына толығымен байланысты, ал жеке секторда дағдылар жалақыны едәуір арттырады. Мемлекеттік және жеке секторларда дағдыларды ескере отырып, ресми білім беруден қайтарымды салыстыруға болады. Бұл, ең алдымен, неғұрлым өнімді қызметкерлердің жеке секторға кетуін туындатады және Қазақстан экономикасының мемлекеттік секторының тиімділігіне күмән тудырады.
Түйін сөздер: білімге оралу, ересектердің дағдылары, функционалдық сауаттылық, Қазақстан, мемлекеттік және жеке сектор.
JEL кодтар: I26, J31, H32

* *Corresponding author: S. Kemelbayeva, s_kemelbayeva@kazguu.kz*

Аннотация. В исследовании рассматривается экономическая отдача от навыков грамотности, счёта и решения задач у взрослых в Казахстане с использованием данных ОЭСР. В отличие от других стран, отдача от навыков не является ни экономически, ни статистически значимой. Этот вывод, однако, полностью обусловлен государственным сектором экономики, в то время как в частном секторе навыки значительно увеличивают заработок. Отдача от формального образования с учетом навыков сопоставима в государственном и частном секторах. Это, вероятно, вызывает отток наиболее продуктивных работников в частный сектор и ставит под вопрос эффективность государственного сектора экономики Казахстана.
Ключевые слова: возвращение к образованию, навыки взрослых, функциональная грамотность, Казахстан, государственный и частный сектор.
JEL коды: I26, J31, H32

Introduction

This study aims to assess economic returns to so-called "functional literacy" in the labor market of Kazakhstan and to provide a comparison with other countries. We measure functional literacy by three skills dimensions introduced by the OECD Program for the International Assessment of Adult Competencies (PIAAC): literacy, numeracy and problem-solving skills in technology-rich environments.

Functional literacy is an important characteristics of an employee. According to the UNESCO definition, "a person who is functionally literate […] can […] engage in all those activities in which literacy is required for effective functioning of his or her group and community and also for enabling him or her to continue to use reading, writing and calculation for his or her own and the community's development"[1]. In a broader context, adult skills are understood as a way of effective socialization in a work and any non-work daily environment. There were three main approaches and methodologies for measuring functional literacy developed by:

- the OECD study "Program for the International Assessment of Adult Competencies (PIAAC)"
- the World Bank's Skills Measurement Program (STEP)
- the UNESCO Institute for Statistics Literacy Assessment and Monitoring Program (LAMP).

In this work, we use PIAAC data due to unavailability of other empirical data for Kazakhstan. Since we measure the literacy of adults, we further use the terms "functional literacy" and "adult literacy" as well as "adult (cognitive) skills" interchangeably.

PIAAC broadly defines literacy as "understanding, evaluating, using and engaging with written text to participate in society, to achieve one's goals and to develop one's knowledge and potential." *(OECD, 2013)*. Literacy skills are the basis for further enhancing participation in modern social life: for instance, the literacy domain includes tasks of understanding a drug label or a digital newspaper article. The Numeracy Score is developed by PIAAC to measure the basic math skills required for work and social life. Numeracy in the PIAAC framework is defined as "the ability to access, use, interpret, and communicate mathematical information and ideas, to engage in and manage mathematical demands of a range of situations in adult life." *(OECD, 2013).* This is measured, for example, by the ability to interpret a numerical information in figures and tables or the evaluation of a special discount offer. PIAAC is the first international survey to implement problem solving in technology-rich environments, that is defined as "using digital technology, communication tools, and networks to acquire and evaluate information, communicate with others, and perform practical tasks." *(OECD, 2013).* Problem solving domain focuses on how people access and make use of information in a computer-based environment, including their ability to use email, fill out digital forms, etc.

Since adult skills, along with other skills, are an important component of the quality of human capital, in Economics there were developed many approaches to assessing this quality, measured mainly through its economic return. There are micro- and macro- levels of economic returns to skills. At the micro level, in turn, it is possible to distinguish individual returns to skills (measured, for example, through wage gains from possession of certain skills or better job prospects, quality of life, etc.), as well as returns at the firm level (increased productivity of firms, which can occur both due to a higher level of proficiency in the skills of their employees, and due to a more

[1] https://learningportal.iiep.unesco.org/en/glossary/

efficient utilization of these skills by companies). The macrolevel represents the returns to the quality of human capital at the country level and is reflected in an increase of macro-indicators such as GDP, labor productivity, employment, and so on. The most researched is the level of individual returns to human capital. Alone with that, it is the key factor, because the productivity and efficiency at the company and country levels depend on the quality of individual human capital.

First research assessing the economic returns to human capital have been carried out in the 1960s by Schultz *(1961)*, Becker *(1962),* and Mincer *(1974).* Schultz stated that the economic growth and prosperity of the countries largely depend not on technological development and resource provision, but primarily on the level of development of the country's human capital *(Davlasheridze, 2010)*. Becker considered skills as an important element of human capital formation: "Human capital refers to the knowledge, information, ideas, skills, and health of individuals. This is the "age of human capital" in the sense that human capital is by far the most important form of capital in modern economies" *(Becker, 2002).* Mincer was the first who developed the so-called "earnings function" according to which individual earnings are considered as the function of education (measured by duration of study or the attained level of education) and experience. This was described in his prominent work "Schooling, Experience and Earnings" *(1974).*

The importance of skills' endowments for today's economies is even greater. Hanushek et al *(2015)* establish them as "as a key ingredient in modern knowledge-based economies". Schwerdt et al emphasize the importance of skills in the context of the skills-biased technological change in the developed and partially developing countries that has taken place over the last few decades. Specifically, they have established a substantial role of skills endowments in economic growth.

While earlier research on human capital mainly focused on studying the general relationship between various economic indicators and education, personal and professional skills, modern research is becoming narrower and more specialized and sophisticated. For example, according to Dajun et al. *(2016),* the observed returns to cognitive skills of women were higher than that of men, and the returns to cognitive skills were higher among blacks and Hispanics than among non-Hispanic whites. This finding is rather universal not only for skills returns but also for schooling returns: a number of research papers found out that minority and disadvantaged groups are those who benefit from schooling and skills improvement to a higher extent than the rest of the population *(Winston, Zimmerman, 2004; Stinebrickner, Stinebrickner, 2006; Garlick, 2018)*. Yao *(2019)* employs the PIAAC data to investigate the earnings inequality as dependent on a major. Reporting that some majors yield systematically higher wages, they conclude that this is caused by initial differences in skills of students selecting into these majors in addition to the differences in educational resources across the majors. Coulon et al *(2007)* exploit a rich dataset generated within the British Cohort Study to estimate the causal impact of basic skills, specifically literacy and numeracy, on earnings. The data allows them to control for possible sources of endogeneity, for example, they control for prior ability. The paper emphasizes several important findings. Firstly, it highlights the importance of prior skills, particularly cognitive skills observed as early as at a primary school – they turned to be the most important determinants of the later-life earnings. Family background, early schooling, and inherent individual characteristics were found to be the key elements of future economic success. Additionally, the authors document that the returns to skills tend to grow in the British labor market over time: in 2004 they turned to be higher than in 1991. The importance of early childhood seems to be important in other developed economies. Murnane et al *(2000)* using the data of the American National Longitudinal Survey of Youth found out that the skills of teenagers are a good predictor of their future earnings.

This study examines the economic returns to skills in a form of marginal earnings for a representative sample of employees in Kazakhstan and other countries collected with the PIAAC study. We estimate the returns to cognitive skills for which we use its proxy – functional literacy - exploiting the basic Mincer's equation. We conduct additional estimations to dig deeper into the observed gap between the returns to skills in the public vs. private sector in Kazakhstan.

The economic returns to skills and schooling in Kazakhstan and abroad

The returns estimates with the basic Mincer's wage model

We replicate the study by Hanushek et al *(2015)* to estimate the economic returns to three dimensions of functional literacy (in accordance with Hanushek, further referred to as "skills") in seven post-Communist countries including Kazakhstan.

Our choice of the countries is rationalized by the fact that these countries, though very different, in recent past had similar labor market structures with the centralized allocation of the labor force, high labor force participation rates, unemployment rates approaching zero, wage grids and compressed wage distribution *(Fleisher, et al., 2005; Münich, et al., 2005).* The returns to education were known to be relatively low in post-Communist countries due to labor market rigidity and official ideology favoring the working class (ibid.); albeit nothing is known about the returns to skills. Moreover, we might expect similarities in the education systems across these countries, specifically, for the existing levels of education, degrees awarded and types of education institutions.

After the fall of the Berlin Wall in 1989 and the further collapse of the Soviet Union, the countries under analysis went through dramatic reforms though with differing speeds and own paths. The next table shows the comparative statistics for these countries.

Table 1 - Comparative statistics

		Czech Republic	Slovak Republic	Slovenia	Poland	Lithuania	Russian Federation	Kazakhstan
1	GDP per capita, PPP (current international $), 1995	13825.9	8676.5	13594.7	7666.7	5916.1	5613.3	5924.8
2	GDP per capita, PPP (current international $), 2017	38824.9	30077.8	36505.7	30064.5	33761.9	25926.4	24863.0
3	Labor force participation rate, (% of total population ages 15-64), 2017	76.11	72.2	74.24	69.85	76.1	74.15	76.38
4	Unemployment, rate (% of total labor force), 2017	2.89	8.13	6.56	4.89	7.07	5.21	4.9
5	School enrolment, tertiary (% gross), 2017	64.1	46.6	78.6	67.8	72.4	81.9	50.1
6	Expenditure on tertiary education (% of government expenditure on education), 2016	12.6	21.3	19.73	22.8	20.5	21.6	11.6
7	Share of public sector in total number of employed	15.4 (2015)	26.9 (2019)	20.9 (2012)	23.6 (2019)	26.9 (2019)	40.6 (2011)	23.3 (2012)
8	PIAAC data: literacy mean score	274	274	256	267	267	275	249
	PIAAC data: numeracy mean score	206	276	258	260	267	270	247
	PIAAC data: problem solving, % at Level 2 or 3	15	26	25	19	18	26	16
	Data source: (1-6) – World Bank data; (7) – ILO data; (8) – OECD, 2019							

Former Soviet republics (Lithuania, Russian Federation, and Kazakhstan) that lagged behind their Eastern European counterparts in terms of GDP per capita in the mid-1990s, almost caught up with them 20 years later. The labor force participation rate in 2017 is also comparable and relatively high, while the unemployment rate is somewhat diverse. Tertiary education enrolment ratio computed as a share of students in a population of relevant age is the lowest in Kazakhstan among the countries under analysis. However, one should keep in mind that the country experienced a dramatic increase in both supply and demand of higher education over the period of independence. Among the post-Soviet bloc countries, it eventually appeared as the country with the greatest higher education enrolment *(Smolentseva, 2012)*. Along with that, expenditures on tertiary education are among the smallest in Kazakhstan relative to other former Communist bloc countries. These two factors likely contributed to the relatively low quality of the tertiary education observed with PIAAC study where Kazakhstan, despite demonstrating an internationally comparable level of adults' skills, was found to be a country with the lowest difference in proficiency between people with compulsory secondary education and professional tertiary education (second such country is found to be the Russian Federation). This observed low quality of tertiary education might negatively affect the returns to education, positively affect the returns to skills and lead to so-called over-education when the supply of people with tertiary education exceeds the demand for them on a labor market. An attempt to test these hypotheses motivates this study.

The research question we address with this empirical exercise is formulated as follows: we seek to estimate the returns to skills in Kazakhstan fitting them into the context of other post-Communist countries and elaborate on differences observed with the estimations. In addition to the returns to skills, we examine the returns to schooling. These two are highly related because skills themselves are partially obtained during schooling; on the other hand, when it comes to tertiary education, education institutions usually select applicants based on their observed skills.

Following Hanushek et al *(2015)* we estimate the returns to skills with the basic Mincer's equation well-known in Labor Economics and tested in many contexts and with many datasets. Despite being "old", the model in the words of Card *(1999)* is "alive and well". Assuming the log of earnings as being dependent on one's education, experience and other individual characteristics having a systematic effect on wage distributions, in its "classical" version, it allows estimating the returns to education. They, in turn, have crucial importance as a factor affecting the behavior of economic agents making decisions on a labor market and a market of education. Hanushek suggests using canonical Mincer's model to estimate the returns to skills for which a rich dataset became available with the PIAAC study. We employ the same model as Hanushek et al *(2015)* to compare the estimates for Kazakhstan not only with another six post-Communist countries selected for analysis but also with the developed countries, returns for which have been estimated in the paper.

We adopt the following specification:

$$lnY_i = \beta_0 + \beta_1 C_i + \beta_2 S_i + \beta_3 E_i + \beta_4 E_i^2 + \beta_5 G_i + \varepsilon_i$$

where:

Y_i - hourly earnings excluding bonuses for wage and salary earners, PPP corrected $US;

C_i - individual skills measured by literacy, numeracy and problem-solving proficiency scores standardized within the country;

S_i - derived variable on total years of schooling during lifetime;

E_i – experience measured by the years of paid work during lifetime;

G_i – gender;

β_1 – returns to skills;

β_2 – returns to schooling.

We estimate this model separately for literacy, numeracy and problem-solving proficiency scores.

We used the data on full-time employees with trimmed highest and lowest wage distribution percentiles (according to Hanushek's methodology) where the "full-time employee", in conformity with the paper, we define "as those working at least 30 h per week" *(Hanushek et al, 2015, p. 109)*. The sample of Kazakhstan consists of 2441 such individuals. 55% of them are females and

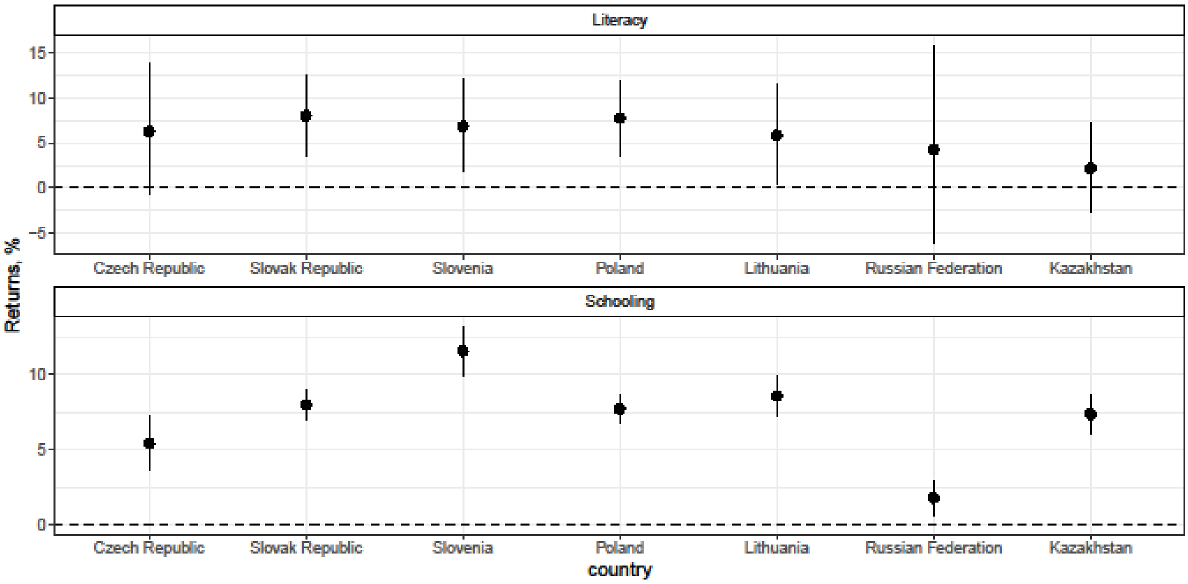
45% are males. 1532 (or 63%) of them worked in the private sector; 896 (or 37%) – in the public sector and the remaining few individuals represent the sector of non-profit organizations. This fairly mirrors the population distribution, where according to the Bureau of National Statistics, the share of employed by the private sector comprised around 70% at the year of survey.

Figures 1-3 display the returns to skills as a percentage change in wages for three skills dimensions, along with the returns to schooling computed with the corresponding specifications for all seven countries.

Almost in all countries (with a notable exception of the Russian Federation[2]), the returns to schooling were found to be robust, relatively high, internationally comparable. In Kazakhstan they are also compatible with the previous estimations *(Arabsheibani & Mussurov, 2007; Kemelbayeva, 2020)*: one additional year of study increases earnings by approx. 7%. This suggests that higher education, for example, in comparison with secondary education provides on average about 28% higher earnings while accounting on skills. Interestingly, the returns to schooling increase only marginally in the same regression excluding the skills proficiency scores – to about 8% or by 14 p.p.

The picture for skills is much more mixed. Likewise in the developed countries *(Hanushek et al, 2015),* in five out of seven developing countries, the returns to skills (specifically, numeracy skills) turned to be higher than the returns to schooling. Two notable exemptions are Slovenia and Kazakhstan where the returns to schooling were found to be much higher than the returns to skills.

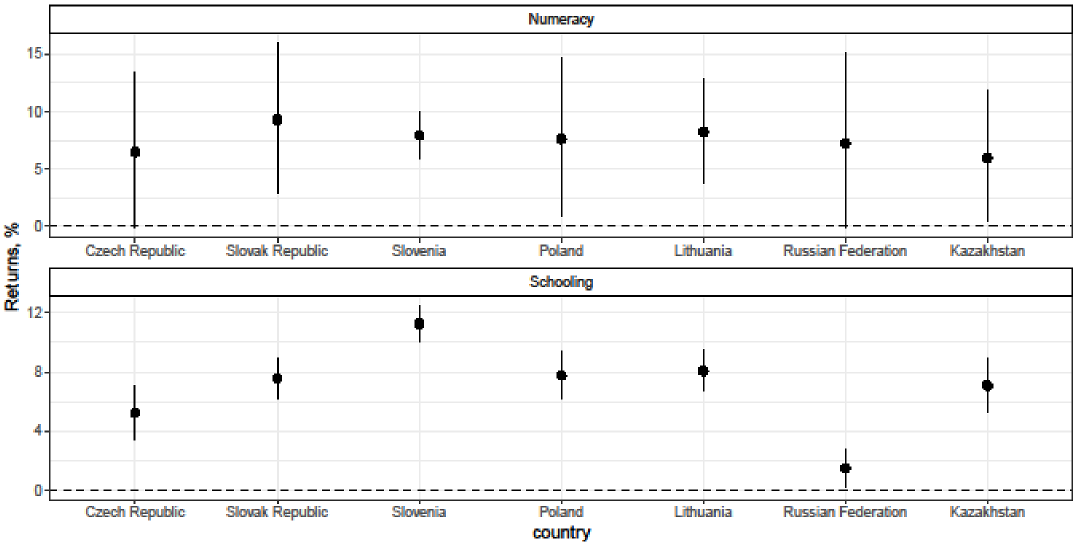
In Kazakhstan, among skills, only numeracy turned to be statistically significant: one standard deviation higher numeracy proficiency score improves the earnings approximately by 6%. The difference in earnings between someone with the lowest numeracy proficiency score (about 3.8 s.d. below the mean) and someone with the highest one (about 3.2 s.d. above the mean) comprises around 42%. The returns to numeracy skills more substantially improve with the schooling variable dropped from the regression – to 8.4% or by 40 p.p. This suggests that in Kazakhstan a larger part of the wage returns is in fact provided by schooling rather than skills.



Note: the figure displays the returns to literacy skills and schooling estimates derived from the regression coefficients with their 95% confidence intervals.

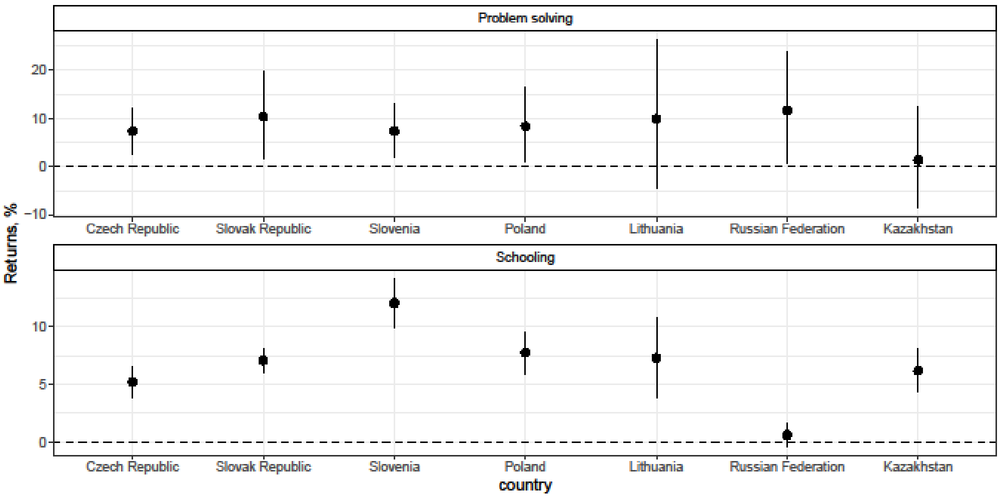
Figure 1 – Returns to literacy skills and schooling

[2]In Russian Federation the estimates are expected to be biased due to exclusion of the capital city (Technical Report of the Survey of Adult Skills (PIAAC)).



Note: the figure displays the returns to literacy skills and schooling estimates derived from the regression coefficients with their 95% confidence intervals.

Figure 2 – Returns to numeracy skills and schooling



Note: the figure displays the returns to literacy skills and schooling estimates derived from the regression coefficients with their 95% confidence intervals.

Figure 3 - Returns to problem solving skills and schooling

According to Hanushek et al *(2015),* schooling and skills were found to be highly correlated in the developed countries: the correlation coefficient between numeracy skills and years of schooling is 0.44. This is found to be the case for the post-Communist countries under analysis, except for Kazakhstan and Russia, as the table 2 suggests.

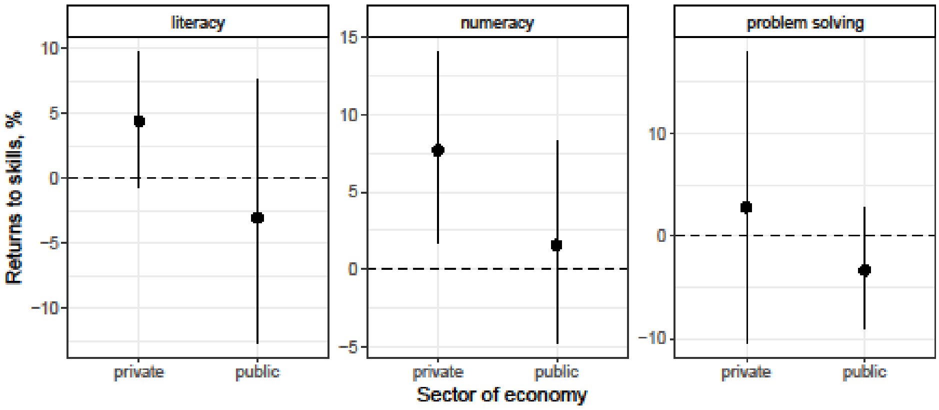
Table 2 – Correlation between years of schooling and numeracy

Country	Correlation coefficient between years of schooling and numeracy
Czech Republic	0.44***
Slovak Republic	0.47***
Slovenia	0.51***
Poland	0.39***
Lithuania	0.36***

Russian Federation	0.22***
Kazakhstan	0.15***
*Notes: table presents the results of Pearson correlation coefficient. Signif. signs: *p<0.1; **p<0.05; ***p<0.01*	

In Kazakhstan, the correlation coefficient is only around 0.15 though positive and statistically significant. On the one hand, this likely captures higher selectivity of tertiary education institutions in developed countries and Eastern European post-Communist countries which more thoroughly select applicants based on their functional literacy, unlike the education institutions in Kazakhstan. On the other hand, a weak correlation between education and skills reconfirms a low quality of tertiary education that does not improve skills, since skills themselves should be upgraded by education.

To understand the nature of the returns to skills in the context of Kazakhstan, we disaggregate the sample by the sector of employment and run the same regressions separately for the public and the private sectors' employees. The results from these regressions are shown in the next figure.



Note: the figure displays the returns to education estimates derived from the regression coefficients with their 95% confidence intervals from models controlling for proficiency in specific skills dimensions separately for two sectors.

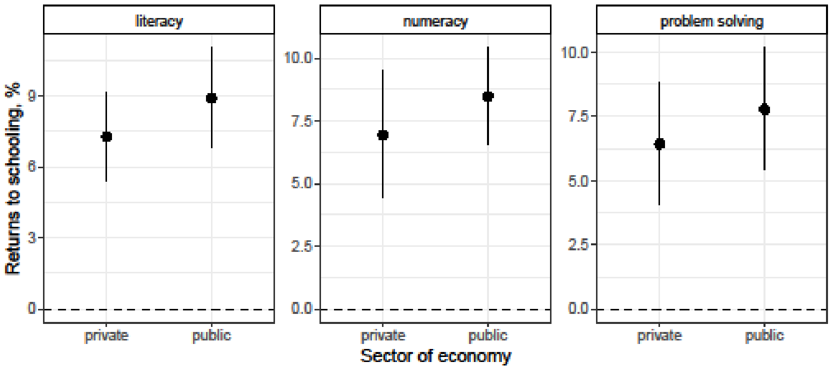
Figure 4 - Returns to skills in Kazakhstan by the sector of economy

As it is clearly seen from figure 4, the numeracy skills returns' premium is fully driven by the private sector. All three types of skills provide relatively high returns to skills in the private sector, though the coefficients for literacy and problem solving are not statistically significant. Along with that, in the public sector the returns to skills are statistically insignificant, low, and – for literacy and problem-solving – even negative. The latter observation should be interpreted in a bizarre way: one standard deviation higher literacy skills are associated with about 2.5% lower wages (though this result is anyway statistically insignificant).

Lower returns to skills in the public sector are often the case in many countries due to the rigidity of the wages in the public sector. For example, Hanushek et al *(2015)* found the returns to skills being systematically lower in countries with the larger public sector. In Kazakhstan, however, this difference is particularly striking. Moreover, the public sector does not play a substantial role in the Kazakhstani economy nor in terms of GDP neither in terms of employment making the observed low returns to skills at the level of the national economy specifically intriguing.

Along with that, the returns to schooling were found to be systematically higher in the public sector than in the private sector, as is seen from figure 5. This likely suggests that selection into employment in the public sector is based on consideration of formal education, and education certificate (diploma) serves as a formal "pass" to a workplace, while in the private sector it is both schooling and skills that drive the selection.

There are other possible interpretations for the observed zero or negative returns to skills in the public sector versus positive returns observed in the private sector. Firstly, while selection by the companies might take place, self-selection of (better-skilled) employees might also be the case. The wages in the private sector in our sample are higher than the wages in the public sector (by 0.07 log points or 0.41 USD per hour); this is confirmed by the national statistics. Secondly, the observed phenomena might reflect the low quality of tertiary education in Kazakhstan reported by PIAAC *(OECD, 2019)* that the private sector companies that are more flexible in terms of hiring and firing and wage policies seek to compensate by the better initial skills of their employees. Finally, it is natural to expect a two-way causality between wages and skills, specifically when the skills obtained on the job are considered. Paraphrasing Hanushek et al, "good" jobs themselves reinforce skills by promoting and refining their use, while "bad" jobs, on contrary, might cause skills' depreciation.



Note: the figure displays the returns to education estimates derived from the regression coefficients with their 95% confidence intervals from models controlling for proficiency in specific skills dimensions separately for two sectors.

Figure 5 - Returns to schooling in Kazakhstan by the sector of economy

The data at hand does not allow to disentangle these possible routes effectively, however, the consequences of the observed phenomena are rather straightforward and concerning. It is suggestive that the redistribution of the abler and potentially more productive workers from the public to the private sector could take place or already takes place. This, in turn, should negatively affect the productivity of the public sector in the long run.

The returns estimates with matching and Mincer wage model

In addition to computing the returns to skills, we compute the returns to schooling in a "classical" Mincerian fashion but not contaminated by presumed omitted variable bias. For that, we follow a two-stage design: on the first stage we match individuals according to their skills with the propensity score matching technique; on the second stage we re-estimate the wage equation on the matched sample.

For matching, we use 10 plausible values for numeracy and literacy (problem-solving is excluded due to many missing values). Our treatment status is a dummy variable separating people with education below and above higher. In each of these groups, we find "twins" based on observed numeracy and literacy skills. We run this model separately for the private and public sectors.

In a sample of 1522 private-sector employees, 438 have attained higher education and above, and the remaining 1084 have below higher education. The difference in hourly earnings between these two groups comprises 1.73 PPP corrected USD (mean earning of people with higher education is 6.14 USD and mean earning of people with education below higher is 4.41 USD) and it is statistically significant with a corresponding t-statistic of 11.38.

The matched sample for the private sector consists of 878 individuals (for each of 439 individuals with attained higher education and above the matching algorithm matched 439 those having education below higher but with very similar PVs on numeracy and literacy). The difference in hourly earnings for this matched sample increases to 1.91 PPP corrected USD (6.14 and 4.22 USD, respectively) suggesting that the returns to education should be higher for this adjusted sample. Indeed, as Table 2 shows the returns to schooling grew in a sample of matched individuals for the private sector from 7.91% to 9.15% for an additional year of study.

The public sector employee comprises 890 individuals; among them, 457 have higher education and above. Thus, the public sector employees in our sample are generally more educated with the share of those with at least higher education attained comprising 51%, as opposed to 29% in the private sector sample. Though the distribution of the earnings is nearly the same for the sectors of employment, as seen from figure 6, the difference in average earnings among the two education groups is smaller for the public sector - 1.58 PPP corrected USD (mean earning of people with higher education is 5.26 USD and mean earning of people with education below higher is 3.68 USD) and it is statistically significant with the corresponding t-statistic of 11.54. After matching 433 individuals with below higher education with those with higher education and above, we ended up with a sample of 866 public sector employees. The difference in hourly earnings slightly drops to 1.55 PPP corrected USD (5.23 and 3.69, respectively).

The results in table 3 are intriguing. For the private sector employees, the returns to schooling in the matched sample increased reaching the magnitude of the returns to schooling for the public sector employees. Thus, on average, the returns to schooling are lower in the private sector in comparison with the public sector while the returns to skills are higher, but when we compare private-sector employees with *the same level* of numeracy and literacy skills, the returns to schooling for them are in fact not lower than in the public sector.

This is not the case for public sector employees. For them, the returns to schooling almost do not change in the matched sample; thus, this reinforces our previous finding that the skills' endowments do not play any significant role for a public sector employee in terms of his or her earnings. The returns to a degree in comparison with below higher education are also fairly similar in the private and public sector employees: a person with a university degree earns around 47% higher salary than a person without a university degree but with the same level of skills.

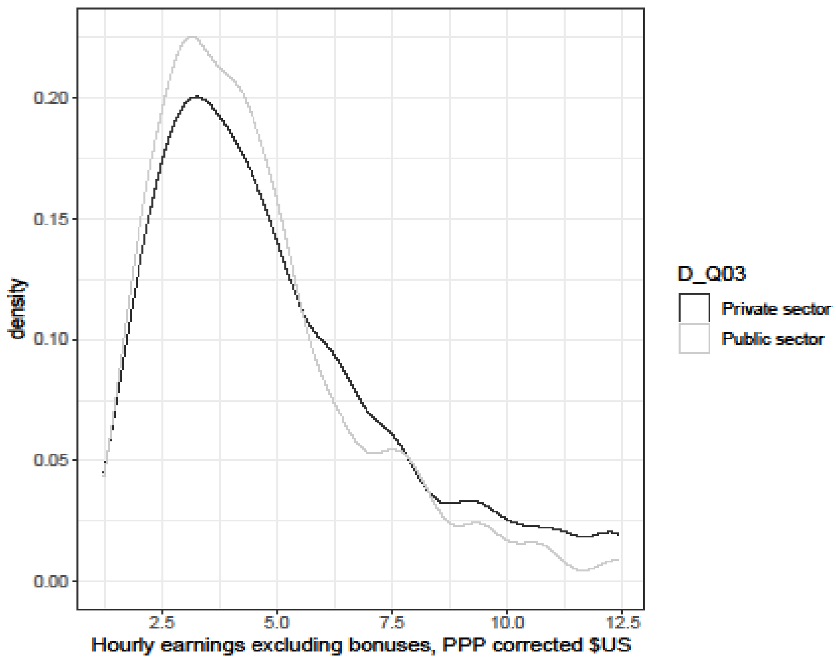


Figure 6 - Density plots for earnings by the sector of economy

Table 3 – Regression results

	Dependent variable:					
	ln(earnings)					
	Private sector employees			Public sector employees		
	(1)	(2)	(3)	(1)	(2)	(3)
Schooling	0.076***	0.088***		0.089***	0.087***	
	(0.006)	(0.007)		(0.007)	(0.007)	
Education			0.388***			0.386***
			(0.033)			(0.029)
Experience	0.007	0.013**	0.008	0.008	0.006	0.007
	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Experience^2	-0.000	-0.000***	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender	-0.136***	-0.125***	-0.114***	-0.155***	-0.151***	-0.140***
	(0.024)	(0.033)	(0.033)	(0.034)	(0.035)	(0.035)
Obs.	1522	878	878	890	866	866
Adjusted R^2	0.1005	0.1434	0.1418	0.171	0.1628	0.172
F Statistic	43.94***	38.56***	37.94***	43.32***	39.92***	46.84***

Notes: table presents the results of three specifications: (1) returns to schooling for initial data; (2) returns to schooling for matched sample; (3) returns to higher education and above for matched sample.

Heteroscedasticity robust standard errors estimated in R with "estimatr" package in parenthesis (Blair et al, 2021). Matching is performed with R "MatchIt" package (Ho et al, 2011). Intercept is not reported.

Ref. category for gender: female; ref. category for education: higher education and above.

*Signif. signs: *p<0.1; **p<0.05; ***p<0.01*

Conclusion

The study explores the link between labor income and skills in Kazakhstan to contrast and compare it with other countries, specifically the Easter European post-Communist countries (for which the analysis was provided by the authors) and the developed countries *(for which we rely on the prominent paper of Hanushek et al, 2015).*

Both in developed and former Communist block countries, cognitive skills were found to be an important determinant of earnings. In developed economies, one standard deviation increase in numeracy provides around 18% higher wages *(Hanushek et al, 2015),* the estimate is lower in post-Communist economies – around 8%. Other skills dimensions are highly correlated with numeracy and assumed to yield somewhat similar returns. This is likely the case for the former Communist block economies, with a notable exception of the Russian Federation and Kazakhstan. In Kazakhstan, only numeracy was found to be somewhat positive though the coefficient approaches acceptable significance level: one standard deviation higher numeracy score provides around 6% higher wages while literacy and problem-solving do not contribute to the earnings.

However, the returns to formal education in Kazakhstan turned to be among the highest within the countries under analysis. With this, within PIAAC cross-country comparisons, Kazakhstan appears as one of the outlier countries where the labor market values education higher than cognitive skills. Relatively high returns to education are often the case for developing countries with a relatively low level of accumulation of human capital, which is likely not the case in Kazakhstan. This result is especially surprising considering the perceived relatively low quality of tertiary education in Kazakhstan confirmed by the PIAAC study.

Moreover, the correlation between formal education (measured by the years of schooling) and cognitive skills were found to be among the smallest in Kazakhstan. We tend to interpret this result as follows: on the one hand, it might capture higher selectivity of tertiary education institutions in developed countries and Eastern European post-Communist countries in comparison with Kazakhstan where individuals with the relatively low skills endowments might enter tertiary education; on the other hand, it again suggests a low quality of tertiary education in

Kazakhstan that does not improve skills.

Finally, our study revealed that the returns to cognitive skills are only the case for the private but not the public sector of Kazakhstan's economy. In the latter, the returns to skills are found to be zero or even negative. With the data at hand, it is difficult to understand what drives this result: self-selection of better-skilled employees to the private sector generating higher wages; more thorough selection into employment by the private sector employers for whom education per se matters less than the skills endowments of a potential employee; the concentration of "better" jobs in the private sector whereby a "better" job we assume the job that more efficiently utilizes the skills and promotes skills' enhancement; higher flexibility and profit orientation of the private sector companies; or all these factors together. At the same time, the returns to schooling were found to be higher in the public sector; however, they fully vanish in the models that explicitly control for skills. When we compare employees with the same level of numeracy and literacy skills, the returns to education in the private sector turned to be the same as in the public sector.

Though it is not easy to disentangle possible roots of the skills returns premia in the private vs. public sector, the consequences are rather straightforward. For both more educated and more skilled employees, employment in the private sector is more lucrative. This creates incentives for redistribution of potentially more productive workers from the public to the private sector and jeopardizes the productiveness of the public sector in the long run.

Авторы выражают благодарность Комитету науки Министерства образования и науки Республики Казахстан за финансирование (Программно-целевое финансирование №OR11465485).

REFERENCES

Felstead, A., Gallie, D., Green, F., Zhou, Y. (2007). *Skills at Work, 1986 to 2006*, ESRC Centre on Skills, Knowledge and Organisational Performance based at the Universities of Oxford and Cardiff.

Arabsheibani, G. R., & Mussurov, A. (2007). Returns to schooling in kazakhstan: Ols and instrumental variables approach 1. *Economics of Transition*, 15(2), 341-364.

Becker, G. S. (2002). *The age of human capital.*

Becker, G. S. (1975). *Human capital: A theoretical and empirical analysis, with special reference to education*. New York: National Berau of Economic Research: Columbia University Press.

Card, D. (1999). The causal effect of education on earnings. *Handbook of Labor Economics*, 3, 1801-1863.

Daniel E. Ho, Kosuke, I., Gary, K., Elizabeth A. S. (2011). MatchIt: Nonparametric Preprocessing for Parametric Causal Inference. *Journal of Statistical Software*, Vol. 42, No. 8, pp. 1-28. url: https://www.jstatsoft.org/v42/i08/

De Coulon, A., Marcenaro-Gutierrez, O., Vignoles, A. (2007). *The value of basic skills in the British labour market* (No. 77). Centre for the Economics of Education, London School of Economics and Political Science.

Fleisher, B. M., Sabirianova, K., Wang, X. (2005). Returns to skills and the speed of reforms: Evidence from Central and Eastern Europe, China, and Russia. *Journal of Comparative Economics*, 33(2), 351-370.

Garlick, Robert. 2018. "Academic Peer Effects with Different Group Assignment Rules: Residential Tracking Versus Random Assignment." *American Economic Journal: Applied Economics.* 10 (3), 345–369. doi:10.1257/app.20160626

Blair, G., Cooper, J., Coppock, A., Humphreys, M., Sonnet, L. (2021). *Estimatr: Fast Estimators for Design-Based Inference. R package version 0.30.2*. url: https://CRAN.R-project.org/package=estimatr

Hampf, F., Wiederhold, S., Woessmann, L., (2017), Skills, Earnings, and Employment: Exploring Causality in the Estimation of Returns to Skills. *Large-scale Assessments in Education*, 5.

Hanushek, E. A., Schwerdt, G., Wiederhold, S., Woessmann, L. (2015). Returns to skills around the world: Evidence from PIAAC. *European Economic Review*, 73, 103-130.

Lawrence, K, Murphy, K. (1992). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *Quarterly Journal of Economics*, 107, 35-78.

Kemelbayeva, S. (2020). Returns to schooling in Kazakhstan: an update using a pseudo-panel approach. *Eurasian Economic Review*, 10(3), 437-487.

Keslair, F., Paccagnella, M, OECD (2020), Assessing adults' skills on a global scale: A joint analysis of results from PIAAC and STEP, *OECD Education Working Papers*, No. 230, OECD Publishing, Paris,

https://doi.org/10.1787/ae2f95d5-en
Dajun, L., Randall, L., Christopher, R.J. (2016). Cognitive Performance and Labor Market Outcomes, *IZA Discussion Papers* 10075, Institute of Labor Economics (IZA)
Mincer, J. (1974). Schooling, experience, and earnings. *Human behavior and social institutions, 2*. New York: National Bureau of Economic Research; distributed by Columbia University Press.
Münich, D., Svejnar, J., Terrell, K. (2005). Returns to human capital under the communist wage grid and during the transition to a market economy. *Review of Economics and Statistics*, 87(1), 100-123.
Murnane, R.J., Willett, J.B., Braatz, M.J., Duhaldeborde, Y. (2001). Do different dimensions of male high school students' skills predict labor market success a decade later? Evidence from the NLSY. *Economics of Education Review*, 20(4), 311-320.
Davlasheridze, N. (2010). *The nobel prize winner in economics theodor schultz about the role of the human capital in overcoming of poverty problems*, Working Paper.
OECD (2013), *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills*, OECD Publishing. http://dx.doi.org/10.1787/9789264204256-e
OECD (2016), *The Survey of Adult Skills: Reader's Companion, Second Edition, OECD Skills Studies*, OECD Publishing, Paris. http://dx.doi.org/10.1787/9789264258075-en
OECD (2019), *Skills Matter: Additional Results from the Survey of Adult Skills, OECD Skills Studies*, OECD Publishing, Paris, https://doi.org/10.1787/1f029d8f-en
OECD (2021), *Management, skills and productivity*, *OECD science, Technology and industry policy papers*, https://doi.org/10.1787/007f399e-en
OECD (2021), *OECD Skills Strategy Kazakhstan: Assessment and Recommendations, OECD Skills Studies*, OECD Publishing, Paris, https://doi.org/10.1787/39629b47-en
Schultz, T.W. (1960). Capital Formation by Education. *Journal of Political Economy*. 68 (6), pp. 571-583.
Schultz, T.W. (1961). Investment in Human Capital. *The American Economic Review.* 51(1), pp. 1-17
Schwerdt, G., Wiederhold, S., Murray, T. S. (2020). *Literacy and growth: New evidence from PIAAC*.
Felstead, A., Gallie, D., Green, F., Zhou, Y., (2007). *Skills at Work, 1986 to 2006*. SKOPE, University of Oxford, 192 pp.
Smolentseva, A. (2012). Access to higher education in the post-Soviet States: Between Soviet legacy and global challenges. *Paper commissioned and presented at Salzburg Global Seminar*. Vol. 495, pp. 2-7
Stinebrickner, R., Todd R. Stinebrickner. (2006). What Can Be Learned About Peer Effects Using College Roommates? Evidence from New Survey Data and Students from Disadvantaged Backgrounds. *Journal of Public Economics.* 90 (8), 1435–1454, doi:10.1016/j.jpubeco.2006.03.002
Winston, G., Zimmerman, D. (2004). Peer Effects in Higher Education. *College Choices: The Economics of Where To Go, When To Go, and How To Pay for it*, 395–424. Chicago: U Chicago Press.
World Bank. (2010). *Stepping Up Skills for More Jobs and Higher Productivity*, World Bank Group, Washington, DC.
Yao, K. (2019). Heterogeneous skill distribution and college major: evidence from PIAAC. *Journal of Applied Economics*, 22(1), 504-526.

ХАЛЫҚАРАЛЫҚ САЛЫСТЫРУ КОНТЕКСТІНДЕГІ ҚАЗАҚСТАНДАҒЫ ДАҒДЫЛАРДЫҢ ЭКОНОМИКАЛЫҚ ҚАЙТАРЫМЫ

Сауле КЕМЕЛЬБАЕВА, *экономика ғылымдарының докторы (PhD), қауымдастырылған профессор, Халықаралық экономика мектебі, М. Нәрікбаев атындағы КАЗГЮУ Университеті, Нұр-Сұлтан қ., Қазақстан Республикасы, s_kemelbayeva@kazguu.kz, ORCID: 0000-0002-7406-0589, ScopusID: 57216337017*
Кайдар НУРУМОВ, *саяси ғылымдар магистрі, аға талдаушы, «Ақпараттық-талдау орталығы» АҚ, Нұр-Сұлтан қ., Қазақстан Республикасы, kaidar.nurumov@iac.kz, ORCID: 0000-0002-1514-0095, ScopusID: 57264987100*
Азат АЙТУАР, *экономика ғылымдарының докторы (PhD), ассистент-профессор, Халықаралық экономика мектебі, М. Нәрікбаев атындағы КАЗГЮУ Университеті, Нұр-Сұлтан қ., Қазақстан Республикасы, a.aituar@kazguu.kz, ORCID: 0000-0002-7625 -8783, ScopusID: 57280245800*
Еркежан ДЮСЕНБЕКОВА, *магистрант, Халықаралық экономика мектебі, М. Нәрікбаев атындағы КАЗГЮУ Университеті, Нұр-Сұлтан қ., Қазақстан Республикасы, ye_dyussenbekova@kazguu.kz*

ЭКОНОМИЧЕСКАЯ ОТДАЧА ОТ НАВЫКОВ В КАЗАХСТАНЕ В КОНТЕКСТЕ МЕЖДУНАРОДНЫХ СРАВНЕНИЙ

Сауле КЕМЕЛЬБАЕВА*, PhD по экономике, ассоциированный профессор, Международная школа*

экономики, Университет КАЗГЮУ им. М. Нарикбаева, г. Нур-Султан, Республика Казахстан, s_kemelbayeva@kazguu.kz, ORCID: 0000-0002-7406-0589 , ScopusID: 57216337017
Кайдар НУРУМОВ, *магистр политических наук, старший аналитик, АО «Информационно-аналитический центр», Нур-Султан, Республика Казахстан, kaidar.nurumov@iac.kz, ORCID: 0000-0002-1514-0095, ScopusID: 57264987100*
Азат АЙТУАР*, PhD по экономике, ассистент-профессор, Международная школа экономики, Университет КАЗГЮУ им. М. Нарикбаева, г. Нур-Султан, Республика Казахстан, a.aituar@kazguu.kz, ORCID: 0000-0002-7625 -8783, ScopusID: 57280245800*
Еркежан ДЮСЕНБЕКОВА*, магистрант, Международная школа экономики, Университет КАЗГЮУ им. М. Нарикбаева, г. Нур-Султан, Республика Казахстан, ye_dyussenbekova@kazguu.kz.*