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DISCUSSION PAPER SERIES

IZA DP No. 17875

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ABSTRACT

Wage Profiles in STEM and Non-STEM Careers

We compare wage profiles for STEM-educated and non-STEM-educated individuals over their lifetimes. Using repeated cross-sectional data from Russia, we examine how the dynamics of these types of human capital are affected by technological developments, applying the Age-Period-Cohort decomposition to workers' life cycle wage growth. Additionally, we account for heterogeneity in the impact of institutional quality on lifetime wage profiles. We show that STEM education is associated with flatter wage-experience profiles than non-STEM education, with the most pronounced differences observed among females. The cohort effect, apparently specific to the former Soviet-type economies, reveals itself in devaluing some types of older education, putting non-STEM cohorts educated during the Soviet period at a disadvantage relative to those with STEM education. Importantly, in the Russian case, the age/experience effects act in the direction opposite to the cohort effects, rendering the cross-sectional analysis somewhat misleading. Finally, wage-experience profiles for males with non-STEM education are steeper in regions with weak institutions than in regions with stronger institutions.

JEL Classification: E24, J24, J31, O33, O43

Keywords: human capital, wage, life-cycle wage growth, age-period-cohort decomposition, STEM, Russia

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Introduction

There is a large literature estimating returns to education and experience, including studies that emphasize heterogeneity among returns to different fields of knowledge. Most of these studies conflate the effect of age/experience and year with the impact of the birth cohort of the individuals because separating these effects is challenging. The approaches proposed by Hall (1968) and Deaton (1997) are quite ad hoc and have not been widely used in the literature. The relatively recent study by Lagakos et al. (2018) proposes a methodology grounded in human capital theory to separate experience, time, and cohort effects and provides estimates for wage-experience profiles for various countries. However, Lagakos et al. (2018) do not apply their methodology for estimating the returns to experience and cohorts in different educational fields. Although the literature has recognized that returns to experience can depend significantly on the area of knowledge such as STEM vs. non-STEM (see below), the potential differences in cohort effects have received little attention. We argue, however, that in some circumstances cohorts can affect different types of education quite differently. Additionally, the existing literature concerned with heterogeneity of returns to different types of skills usually does not address the impact of institutional quality on these returns.[1] In this paper, we apply the methodology developed by Lagakos et al. (2018) to compare wage profiles for STEM-educated and non-STEM educated individuals in Russia – a country that undergone deep structural changes in its economy and educational system – and show that both cohorts and institutional quality can have significant impact on wage profiles.

What makes lifetime wage profiles of STEM-educated workers different from those of their non-STEM counterparts? STEM human capital complements technology, which tends to advance rapidly. This rapid advancement exposes scientists and engineers to additional risks of obsolescence (Ryoo & Rosen, 2004; Deming & Noray, 2020). On one hand, STEM skills acquired by older cohorts during formal education and early adulthood tend to become outdated. On the other hand, as workers age, cognitive capacity and health tend to deteriorate, increasing the cost of retraining while the required "payback" period shortens. Thus, the two effects—biological aging and cohort—affect the stock of skills (Rosen, 1975; Neuman & Weiss, 1995; Lagakos et al., 2018). Although these challenges are relevant for any complex skills, STEM and non-STEM skills differ in their exposure to obsolescence and costs of upgrading. Skills in computer sciences and complex engineering change especially fast (Deming & Noray, 2020). The evolution of wages over the

[1] There is substantial literature that examines returns to wealth-creating vs. rent-seeking skills in different institutional environments (Murphy et al. 1991, Baumol 1990, North 1990, Natkhov and Polishchuk 2019, and Alexeev et al. 2023). However, this literature does not focus on wage-experience profiles or returns differentiated by cohorts.

working life reflects different trajectories of accumulation and depreciation of STEM and non-STEM human capital, making the comparative study of these trajectories particularly salient.

Additional factors specific to countries can affect the accumulation and depreciation of skills. For example, strong and prolong systemic shocks can impact existing human capital stock, affecting both types of obsolescence by devaluing old education and deteriorating health in older ages. Transitions from a planned economy to a market economy, followed by transformational recessions, are among such events.

There is also another aspect of the differences between STEM and non-STEM human capital. As Murphy et al. (1991) and other papers mentioned in footnote 2 argue, STEM activities are more likely to be wealth-creating while at least some non-STEM ones are better suited to rent-seeking and redistribution, more generally. Wealth-creating activities typically provide for higher returns compared to rent-seeking ones in a better institutional environment. Therefore, we would expect a positive relationship between the relative returns to STEM education (as compared to non-STEM one) and institutional quality.

In this paper, we examine workers in Russia, exploring how wages evolve in STEM and non-STEM fields of education over a worker's career. We use the duration of potential labor market experience as a key measure of career-related human capital accumulation.

Russia is particularly interesting for our purposes because, among other factors, it highlights the importance of distinguishing between experience and cohort effects on wage profiles of STEM and non-STEM workers. This distinction becomes especially relevant due to the fundamental structural changes associated with the plan-to-market transition. Russia began its transition journey in 1992, after the collapse of the USSR, and remained in recession throughout the 1990s.[2] The economic boom during the first decade of this century changed the economic structure of the country and partially reshaped the demand for skills. Much of the second decade was spent in economic stagnation (Gimpelson & Kapeliushnikov, 2023). These developments affected both STEM and non-STEM skills, though to different degrees. The sharp structural break due to the transition to a market-oriented economy also implied that both the accumulation and depreciation of skills could be cohort-specific. In particular, while pre-transition STEM knowledge remained relevant to the new economy, much of the non-STEM education acquired in the old system became obsolete. Moreover, Russia is a very large and diverse country, and although its overall institutional quality is rather poor, there is a large diversity of Russia's regions in this respect. Therefore, the Russian data provide an opportunity to explore the impact of both changing

[2] Of course, the Soviet economy and society were in crisis for at least a few years before 1992.

economic structure and diverse institutional environment on wage profiles engendered by STEM vs. non-STEM education. Our testable hypotheses about this impact are developed in Section 4 of the paper.

Besides the issues outlined above, there are a few other country-specific reasons why this can be of interest. First, Russia aims to be a technologically advanced country, at least in the military-industrial part of its economy. Whether this claim is justified is outside the scope of our study. Examining the STEM group provides additional insight into Russia's capacity to keep up with technological progress, produce new technologies, and absorb imported ones. Given the current geopolitical situation this question deserves additional attention.

Second, after Russia's annexation of Crimea in 2014, Western countries launched the first wave of technological and trade sanctions. Russia responded by adopting an import substitution policy aimed at achieving technological independence. The Russian invasion in Ukraine in 2022 led to a comprehensive, albeit poorly enforced, ban on any technological transfer from the West. These sanctions, along with Russian counter-sanctions, strengthened the domestic trend towards technological self-sufficiency and contributed to the accumulation of backwardness. Since modern warfare relies on technologically sophisticated weaponry, having highly skilled scientists and engineers is crucial for producing and supporting related technologies. In order to retain these skilled workers in STEM jobs and motivate them to maintain their human capital and exert effort, they should be paid competitively. Low relative wages induce workers to quit their STEM jobs, destroy motivation, foster opportunism, and lead to negative selection. The current labor market returns to specific majors and jobs, including STEM fields, also influence students' choice of educational major.

The main questions we address in this paper are how STEM and non-STEM wages evolve over labor market experience and how the transition to markets affected cohorts educated in the old system. In particular, do STEM majors provide a wage premium relative to non-STEM alternatives over a working life and whether these relative trends differ between the cohorts educated in the Soviet and post-Soviet times? In addition, we explore the issue of how the life cycle earnings profiles of STEM and non-STEM majors depend on regional institutional quality.

To our knowledge, this is the first study of wage profiles of STEM and non-STEM majors in Russia where the effects of age/experience are separated from those of cohorts. Moreover, this is the first study where wage profiles for STEM and non-STEM workers are examined taking into account institutional quality of the jurisdiction of the worker.

To explore life cycle wage profiles, we separate age/experience and cohort effects using an age-period-cohort (APC) decomposition. We first use the Mincerian-type earnings equation and cross-sectional data to show that in general, STEM specialization (as a college major) provides no significant wage premium over non-STEM, either on average or with experience/age. However, we later demonstrate that the APC decomposition reveals some important differences in wage-experience profiles that are offset by inter-cohort differences. Specifically, we show that STEM education results in flatter wage-experience profiles than non-STEM one, with the most pronounced differences for female workers. Also, we demonstrate that the cohorts educated in non-STEM fields during the Soviet period are at a considerable disadvantage relative to those who received STEM education at the same time. Additionally, we find that wage-experience profiles for males with non-STEM education are considerably steeper in regions with weak institutional quality than in regions with stronger institutions while institutional quality does not appear to affect males with STEM diplomas or females.[3]

This paper is structured as follows: The next section reviews relevant theoretical and empirical literature. Section 3 documents the demand-supply situation of STEM and non-STEM graduates in the Russian economy. Section 4 discusses our hypotheses based on theories of STEM's life cycle wage growth relative to non-STEM. Section 5 describes the data and main variables. Section 6 focuses on the descriptive characteristics of STEM and non-STEM groups. In Section 7, we move from simple cross-sectional wage-experience profiles to decomposition of the wage profiles of STEM and non-STEM groups into age/experience, time, and cohort effects. The final section offers concluding remarks. Some methodological details and additional estimates are relegated to the appendices.

1. Literature Review

Our study relates to three major strands of literature. The first two are more general, while the third is country-specific.

Human Capital Evolution Over the Life Cycle

The first strand explores how human capital evolves over the workers' life cycle. This line of research begins with Mincer (1974) and Ben-Porath (1975). Rosen (1975) identifies two primary reasons for human capital depreciation. The first reason relates to biological aging, as human

[3] The lack of impact of institutions on STEM diploma holders might be due to the fact that rent-seeking activities are usually region specific (one needs to have established local networks, the knowledge of local institutional environment, etc.) while STEM skills can be easily applied in any region.

capabilities diminish with age, affecting speed of physical and cognitive reactions, memory, stamina, dexterity, and general health. The second reason is associated with the emergence and dissemination of new knowledge, which can be termed the vintage effect (Rosen, 1975; Neuman & Weiss, 1995). These two components of human capital depreciation differ in nature and evolve separately, but they are strongly intertwined in the data.

Different cohorts can vary in their rates of human capital depreciation due to factors such as technological progress, advances in healthcare, or other events that affect the current value of skills. With cohort-specific rates of obsolescence, cohorts can exhibit different life-cycle wage profiles. We refer to the cohort-specific component of wage growth as the cohort effect.

In developed market economies, there is little variation in life-cycle profiles by cohorts. However, in emerging economies, frequent shocks of different nature can cause wage profiles to vary considerably across cohorts. Recent studies show that these profiles differ in steepness and shape when the cohort effect is properly separated from that of experience (Fang & Qiu, 2023 on US and China; Gimpelson & Chernina, 2023 on Russia). Moreover, in countries that have undergone a large structural and political change, cohort effects could be different for different types of human capital. None of the studies provide a detailed examination of this possibility.

Returns to Different Types of Human Capital

The second strand of the literature deals with returns to different types of human capital — general versus specialized (industry- or occupation-specific). General education is often viewed as facilitating better adjustment to macro-shocks and structural changes, whereas specialized education does not (Krueger & Kumar, 2004; Kinsler & Pavan, 2015).

STEM education tends to be more applied and specialized than non-STEM one. This eases the school-to-work transition and promises higher starting wages. However, with each technological advance, complementary STEM skills need updating (Deming, 2023). This puts STEM workers in a continuous race with technological change (Goldin & Katz, 2007). As workers age, skills upgrading becomes more costly due to cognitive and health constraints, while the required "pay-back" period to training shortens. Employers also have weak incentives to retrain older workers as new cohorts of freshly educated graduates become available.

Deming and Noray (2020) explore how technical progress in the US updates the composition of tasks and related skills. College STEM graduates start their careers with a higher wage premium compared to non-STEM graduates, but as workers age, skills obsolescence and competitive pressures from younger cohorts erode the premium. The most able STEM workers are more likely to move to managerial or non-STEM jobs when their STEM-related premium evaporates. This outflow from STEM jobs inflates demand for STEM graduates, as firms expecting shortages at the ongoing wage rate post extra vacancies. Resulting STEM and non-STEM age-wage profiles likely mirror different regimes of human capital accumulation and utilization.

An additional factor affecting selection into high-tech jobs relates to the preferences of high-tech startup founders, who are often young, entrepreneurial, and risk-loving (Ouimet & Zarutskie, 2014). Young people prefer their generation as peers. By expanding and winning market niches with high profit margins, such companies pay higher wages, biasing the age profile of STEM workers towards younger groups.

On the other hand, non-STEM skills are typically less technology-dependent, require a longer period to accumulate, but are more resilient to the passage of time.[4] General education leads to a relatively bumpy labor market entry and is likely to be supplemented by additional training before workers achieve high productivity.

STEM- and non-STEM-Related Human Capital in Russia

The third, country-specific strand of the literature examines how STEM-related human capital has been accumulated and utilized in Russia.[5] Academic scholars have primarily focused on the R&D segment of STEM (Ganguli, 2015; Balzer, 2019; Graham, 2013). However, this segment is quantitatively modest, comprising about 7% of total STEM employment (in the ISCO 2 group to which all highly skilled professionals belong) in 2020.[6] Most STEM employment involves all sorts of engineers in industry, construction, transportation, and communications.[7]

Despite large enrollments and a strong tradition in math and engineering, the average quality of engineering education in Russia remains questionable. It can be relatively high in a few elite universities, but major enrollments are in non-elite and low-selectivity institutions, where per capita funding, admission standards, and total R&D expenditures are low (Loyalka et al., 2014). Shmeleva and Frumin (2020) note that, on average, the quality of STEM education is unsatisfactory, and these majors are often chosen by academically weak students. This raises questions about the learning capacity of an average engineering student and whether they lag

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[4] This is consistent with well-known tendencies in evolution of fluid and crystallized intelligence (see, e.g., Cattell, 1971).

[5] There have not been comparable studies in economics of non-STEM human capital in Russia.

[6] Authors' estimates based on 2020 LFS data.

[7] In 2019, the total ISCO-2 group comprised about 24% of all employed individuals in the Russian economy, with one in four professionals belonging to STEM-related occupations. Within this group, engineers of all specializations, except IT, constituted 70%, while the total IT segment, including IT engineers, accounted for an additional 23%. Specialists in Natural Sciences and Mathematics made up the remaining 7% (Rosstat, 2019). Therefore, we will sometimes refer to the entire group as "engineers" since they quantitatively dominate.

behind non-STEM students in observed and unobserved abilities. Even if they do not, it does not guarantee a high level of educational output given modern STEM job requirements.[8]

STEM education supplies labor to various industries. Mining and IT are among the best-paying Russian industries. Defense-oriented manufacturing is a major employer of STEM labor but, at least before the full-scale invasion of Ukraine in 2022, was not paying high wages. Luzin (2020), a leading expert in the field, writes that low profitability, high debt levels, and growing costs are common for Russian defense manufacturers. Labor productivity within the industry is low, with employees in the Russian defense manufacturing holding company (Rostech) producing significantly less per person compared to Lockheed Martin employees. This explains at least in part the low pay for ordinary engineers and the negative implications for their skill accumulation.

Academic studies focusing on STEM wages in Russia are scarce. Denisova and Kartseva (2008) appear to show that, for men, the market value of engineering education is not higher than that of law and economics, while for women it is significantly lower. However, Denisova and Kartseva (2008) do not provide confidence intervals for their results and although the difference for females seems to be substantial for 2000-2004, it disappears in 1998 and 2005. Gimpelson and Zinchenko (2021) compare wages of professionals with and without STEM education, employees in STEM jobs and alternative positions, and various combinations of education and jobs, controlling for major observable characteristics. They find no significant benefits from STEM specialization compared to non-STEM majors and jobs. The premium does not emerge over experience or age; moreover, older groups engaged in STEM-related work tend to experience a wage penalty. As we move from younger to older age cohorts, wage growth declines, meaning that wages for younger cohorts catch up and surpass those of older cohorts, even if initially lower. These results are consistent across all available datasets. However, these studies do not disentangle the effects of experience/age from cohort effects. As we demonstrate below, these effects might be quite different and offset each other.

Finally, Alexeev et al. (2024) show that the choice of major by the higher ability individuals in Russia is strongly influenced by the regional institutional quality. The students with higher scores on the Russian standardized test matriculating in universities in the regions with weaker institutions tend to enroll in such non-STEM majors as law and public administration which are better suited to rent-seeking activities.

[8] Since at least mid-2000s, the test scores from the Unified State Exam for those applying for STEM majors have been significantly below those for many non-STEM applicants (Shmeleva & Frumin, 2020).

2. Examining STEM and non-STEM Through the Lens of Supply and Demand

Relative wages in STEM and non-STEM fields, like any other wages, are market outcomes influenced by supply and demand. An undersupply relative to demand at a given wage drives wages up, and vice versa.[9] In this section, we examine the demand-supply situation in Russia during the period of our wage data. As a measure of supply in STEM and non-STEM areas, we can use the number of workers with education in respective fields in the labor force. The actual number of STEM-related jobs (in the ISCO 2 group) indicates the demand for this type of labor at existing wages; similarly, for non-STEM-related jobs. Both measures are available from the Russian Labor Force Survey (LFS).

Supply and Demand

On the supply side, we examine the stock of STEM graduates, graduates in all fields, and the annual inflow of recent STEM and total graduates.[10] In 2018, the share of STEM graduates among all tertiary-educated individuals aged 25–64 was 29.7%, and among recent graduates in 2017, it was 22.6% (Rosstat, 2019). For comparison, the corresponding figures for the OECD were, on average, 16.2% and 14.2% (Education at a Glance, 2019, Fig. 1A). None of the OECD countries had STEM graduates shares as high as Russia.

Figures 1.1 and 1.2 provide insights into the supply of university graduates to the Russian labor market. Figure 1.1 presents the output of the Russian higher education system from 2005 to 2020, including STEM majors. After peaking in 2010, the number of graduates decreased by about 40%, driven by a sharp demographic contraction in younger cohorts and a deliberate governmental effort to eliminate low-quality colleges. This effort primarily affected non-STEM fields such as economics, law, psychology, and management, while the annual number of STEM graduates remained relatively stable. Each year, around 300,000 young STEM graduates entered the Russian labor market, reflecting the low elasticity of supply of engineers which can result in large wage fluctuations if demand changes significantly. However, as we argue later, this is unlikely to affect the interpretation of our main results in Section 7.

[9] Although the supply-demand relationship clearly influences wages, we will argue that its effect on our main results is unlikely to be large.

[10] Obviously, the difference between total stock/flow and STEM stock/flow represents non-STEM stock/flow.

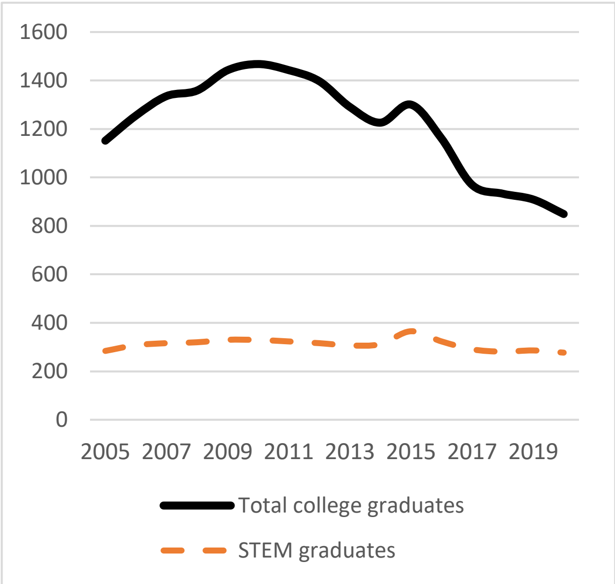

Fig. 1.1. Annual number of college graduates (annual inflow), 2005-2020, thousands.

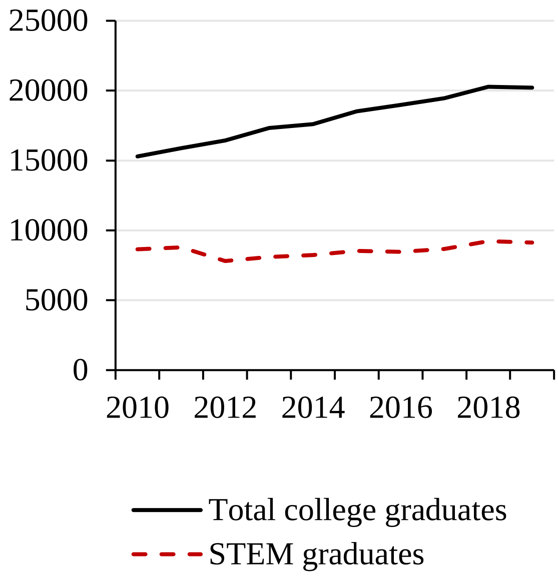

Fig. 1.2. Total number of college graduates in the population (total stock) 20-69 years old, 2010-2019, thousands.

Source: Authors' estimates using Rosstat data.

Figure 1.2 shows the total (accumulated) stock of college graduates, including those with STEM majors whose number has fluctuated within the range of 8 to 9 million individuals aged 20-69.

This supply inflow is large relative to the relevant stock of jobs. Figure 2 shows the total size of the ISCO 2 occupational group (which includes all professionals) and the size of its STEM-related sub-groups. In 2020, all STEM jobs (within the ISCO 2 group) employed about 4.4 million professionals. One sixth of them were 25 to 29 years of age. Over a five-year period, the STEM-related output of Russian educational institutions was twice as large as the number of STEM professionals in this age group. As we move up the age scale, the number of STEM professionals tends to decrease due to outflow to jobs in other sectors (Gimpelson & Zinchenko, 2021). Over time, this outflow remains visible in all annual cross-sections. In 2020, the number of employed individuals in the 45+ age groups was even smaller than in 2005, although the younger groups were much better populated. Thus, more professionals enter STEM jobs at a younger age, but many withdraw from these jobs by mid-career.

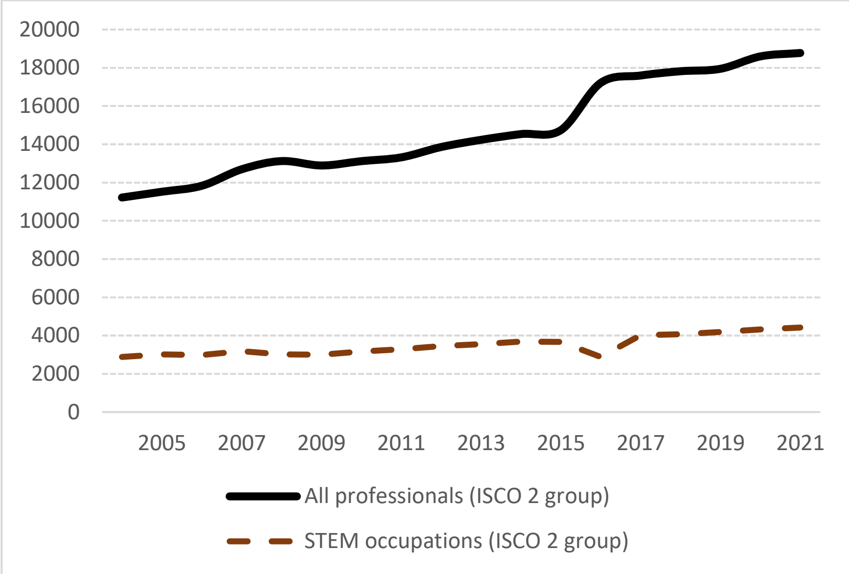

Fig. 2. Total number of professionals (ISCO 2) and STEM professionals, 2004-2021, thousands.

Source: Authors' estimates using Rosstat data.

A simple calculation using 2019 LFS data suggests that the aggregate supply of STEM professionals (in all STEM-related fields) is more than twice the aggregate demand for them. The total number of STEM-educated individuals (aged 25-72) was about 7.4 million, while the total number of relevant jobs in the economy was around 3.3 million. With such a difference, there should be no shortage of certified graduates. However, not all graduates are eager to pursue this career. Additionally, while having formal diplomas, many may lack the necessary skills, making them unemployable as engineers and pushing them out of the STEM sector. Some STEM graduates may also advance to managerial positions, using their acquired STEM skills only partially.

As the above brief discussion shows, a rough quantitative comparison does not suggest any overall undersupply of STEM graduates.[11] Of course, this group is not homogeneous, and there is no full substitutability within the field. Various factors, such as narrow STEM specializations, uneven quality of education and abilities, and heterogeneity in graduates' preferences concerning their professional careers, can play a role in shaping actual supply in specific STEM fields. Potentially, this may result in significant differences between the accumulated number of graduates and the current stock of actual skills.

[11] We do not discuss composition of university graduates by fields and majors.

Theoretical Considerations on STEM and non-STEM Relative Wages

Our further discussion is guided by human capital theory (Becker, 2009; Ben-Porath, 1967; Mincer, 1974; Deming, 2023). Below, we present some key considerations related to our work and hypotheses implied by them.

A worker's wage can be expressed as the product of the human capital stock, h, and its unit rental rate r, or $w = h*r$. If the rental rate is assumed to be constant (as is typical in human capital theory), wage dynamics largely result from changes in the human capital stock (Boulus & Robertson, 2012). However, this stock is heterogeneous and changes over time.

When individuals enter the labor market, they possess knowledge and skills acquired through formal education. In the labor market, they accumulate skills through work experience. This accumulation results from additional investments minus depreciation. Over a career, the balance between investment and depreciation tends to change. The closer a worker is to the end of the career, the smaller the investments in their human capital are and the bigger the depreciation is (Ben-Porath, 1975). This generates an inverted U-shaped wage profile with a flat spot for investments in the pre-retirement period as no new investments are made.

According to the literature reviewed earlier, there are two main factors that generate the loss of human capital:

Biological Aging: This is associated with a decline in cognitive capacity, loss of dexterity, stamina, health, etc. The nature of this type of depreciation is internal and relates to the workers themselves.

Changing Technological Environment: The advancing knowledge frontier can render previously acquired skills obsolete, as they are no longer complementary to new technology. The longer the gap between years in college or other training and years of practical utilization, the higher the risk that skills acquired through formal education are no longer in demand. New technologies require new vintages of skills, rendering old ones obsolete. Rosen (1975) calls this "external devaluation" (see also Deming, 2023). Deep and prolonged systemic shocks can also devalue previously accumulated human capital (Chernina & Gimpelson, 2023).

In our study, college graduates with STEM and non-STEM majors possess comparable amounts of human capital (as measured by level and duration of education) but of different types. However, their lifetime wage profiles are quite different in some cases. We suggest that the difference relates to how STEM and non-STEM skills accumulate and depreciate under the influence of various factors.

1. *Complementarity to technology*. Since skills are complementary to technology, they need to be upgraded simultaneously. Faster technological change requires faster updates, as the growing mismatch threatens employers, technology, and workers. Examples of such mismatches are numerous. For instance, computer-based design systems make hand-drawing skills obsolete. Skills required in a traditional assembly line are of zero value in a fully automated production process. Since technical progress usually affects STEM fields and jobs more strongly than non-STEM ones, the speed of external devaluation for the former is typically higher. Upgrading skills is costly for firms and workers, and these costs rise as the technological frontier is approached. The costs are not just monetary but also intellectual and psychological, and they tend to grow with workers' age. Thus, external devaluation can exacerbate or be exacerbated by internal devaluation. Both types of devaluation reshape the human capital profiles for STEM and non-STEM workers differently (Deming & Noray, 2020; Deming 2023). Specifically, this implies that STEM-educated workers would tend to have flatter wage growth profiles than those in non-STEM fields.

2. *Specific vs. general skills*. STEM skills are more specialized and applied, while non-STEM skills are typically more general. Holders of STEM skills have a shorter school-to-work transition and usually enjoy higher relative wages at the start of their professional careers, but they may fall behind in wage growth as technology changes. For holders of non-STEM skills, the labor market entry phase can be bumpier, as they may need additional training, but more general skills make adjustment to technological upgrades easier and less costly (Kinsler & Pavan, 2015).

Both above considerations imply our first hypothesis (H1): *STEM-educated workers tend to have higher initial wages compared to non-STEM workers, but the wage-experience profile of their earnings is relatively shallow (i.e., flatter) and is more likely to turn negative at the end of their careers*.

3. *Occupational mobility*. When intra-occupational advancement stalls, the most able and quick-learning individuals are incentivized to change occupations. As workers age, occupational mobility becomes more difficult, and STEM and non-STEM specialists can diverge in mobility patterns, with the former being more likely to switch fields of work (Deming & Noray, 2020; Deming 2023). This consideration might also explain the flatter experience earnings profile of STEM-educated workers in our sample.

4. *The effect of a sharp structural change in the Russian economy*. As argued earlier, STEM education in the former USSR was much closer to world standards than non-STEM education. Therefore, STEM skills of older workers would be much easier to adapt to the needs of STEM sectors in the post-Soviet market economy. This implies our second hypothesis (H2): *Within the cohorts educated during the Soviet times, STEM workers would demonstrate higher earnings*

growth profile than the respective non-STEM cohorts, at least relative to the relationship between STEM and non-STEM wage profiles for those educated after the collapse of the USSR.

5. As discussed earlier, returns to different occupations are affected by the institutional quality of the jurisdiction where the person works. Specifically, non-STEM workers are more likely to prosper relative to STEM ones in environments with weaker institutions such as property rights protections and contract enforcement. This consideration generates our third hypothesis (H3): *The wage experience profiles of non-STEM workers will typically be steeper (relative to those of STEM workers) in regions with weaker institutions than in regions with stronger institutions*.

Finally, we note that our hypotheses might apply differently to males and females. Specifically, it is likely that the wage experience profile for women with majors in male-dominated fields such as STEM would be flatter than in other fields (see Maume 1999). Also, Russia's society is in general male-dominated relative to other European countries, which can affect career advancements for males and females (Atencio & Posadas, 2015).

3. Data and Definitions

We focus on the educational major of the individuals in our sample (as opposed to the nature of their job) using the STEM/non-STEM education breakdown.

Our STEM/non-STEM breakdown is still quite aggregated. Being a STEM graduate does not guarantee a perfect job-education match even in a STEM job due to heterogeneity within each group. The same is true for non-STEM graduates. Throughout their careers, individuals can move vertically (along the skills ladder) as well as horizontally (across occupations).

To select STEM-educated individuals, we use the Russian version of the International Classification of Education (ISCED)[12]. If a respondent has more than one college diploma, we prioritize the most recent one. If two diplomas are received in the same year, the STEM major is assigned priority.

We use microdata from the Russia Longitudinal Monitoring Survey - Higher School of Economics (RLMS-HSE).[13] This dataset is nationally representative and contains information on a wide range of socio-economic and demographic characteristics. We utilize data from rounds 2000–2019 to generate repeated cross-sectional data set. Given the significant shocks due to COVID-19 and the

[12] URL: http://uis.unesco.org/sites/default/files/documents/international-standard-classification-of-education-isced-2011-en.pdf

[13] For the RLMS-HSE, see https://rlms-hse.cpc.unc.edu, https://www.hse.ru/org/hse/rlms

full-scale Ukraine war in recent years (2020-2024), which could affect both employment and wages, we decided not to include these rounds.

Our wage measurement uses the RLMS question: "*How much money did you receive in the last 30 days from your primary job after taxes? If you received all or part of the money in foreign currency, please convert that into rubles and report the total*." To account for potential in-kind payments, we add estimates from the question: "*How much does the received product cost regardless of what you did with it*?" Therefore, the monthly earnings are the sum of monetary and non-monetary individual incomes. We then calculate the hourly wage value by dividing the monthly earnings by the number of hours worked, and the natural log of this value is our main variable of interest. We use the annual average wages divided by *typical* working hours as an alternative definition as a robustness check. Wage values are deflated using the annual regional CPI, taking 2019 as the base year. We also make an adjustment for regional price levels using the Rosstat's cost of a fixed basket of consumer goods and services.

Since the RLMS questionnaire does not contain a direct question on post-schooling labor experience, we calculate potential experience using the conventional formula: $exp=age-6-N$, where N is the number of years in full-time education. However, applying this formula to women requires caution. Female employment can include spells of non-employment or part-time employment due to childbirth, which can cause an overestimation of actual labor force duration and bias returns downward. This issue is more germane for non-STEM workers, where the fraction of females is higher.

In our empirical analysis, we focus on workers with university-level diplomas. Our sample consists of respondents aged 21-59 who work full-time, have potential experience of up to 40 years, and are not currently full-time students or early retirement pension recipients. We exclude active military personnel, those working less than 20 hours per week, and observations with missing wage data. Given all the data constraints, our working sample covers 20 annual rounds of the survey and includes approximately 6,000 males and 9,700 females.

We measure the institutional quality of a region using the investment risk index calculated by the rating agency Expert RA. This index was also used by Alexeev et al. (2024) and is arguably the most popular and comprehensive measure of regional institutional quality in Russia.[14] Another advantage of this index is that it is available for all regions. The risk index (we call it *RI*) reflects the quality of regional legislation, financial situation of the region, crime rates, etc.[15] We divide

[14] For a survey of institutional quality measure in Russia see Baranov et al. (2015).

[15] The details of the methodology for constructing the index are available at www.raex-a.ru (in Russian).

the regions in our sample into two groups, assigning the value of 1 to the regions in the bottom half of institutional quality and the value of 0 to the regions in the top half. Our results with respect to the impact of institutional quality should be treated with caution because the RLMS sample is not necessarily regionally representative.

4. Descriptive Characteristics of STEM and Non-STEM Groups

Table 1 provides an initial insight into the heterogeneity of Russian professionals, presenting the key individual characteristics of the respondents averaged over the period 2004–2019.[16] Non-STEM individuals tend to be younger than their STEM counterparts. The fraction of workers aged 50 and over was 1.5-2 times higher (depending on the age group) in STEM than in non-STEM. The majority of respondents were urban and married.

As to the sectoral breakdown, individuals with STEM education were employed predominantly in industry and market services. These two sectors accounted for about 60-70% of all STEM graduates in the economy. Non-STEM individuals, on the other hand, were largely (about 70-80%) employed in market and non-market services. Men with STEM majors tended to be at higher pay levels compared to their non-STEM counterparts. Among women, holders of STEM majors earned significantly less than those with non-STEM majors. Also, there was a gender wage gap in both groups of majors.

Table 1. Descriptive statistics

Characteristics	Women		Men	
	non-STEM-educated	STEM-educated	non-STEM-educated	STEM educated
Average age	36.23	39.26	35.32	38.47
Married, %	63.62	60.12	73.08	81.54
Urban population, %	79.31	85.26	81.65	81.95
Industry groups, %				
Agriculture	1.32	3.65	1.67	4.18
Industry (manufacturing + mining)	11.5	27.97	16.72	37.38
Construction	2.74	7.4	6.64	11.94
Market services	31.46	32.15	35.33	29.72
Non-market services	51.2	26.88	37.97	15.85
Other	1.79	1.96	1.67	0.94
Experience groups, %				
0-9 years	29.2	24.7	37.13	29.12
10-19 years	35.62	25.95	37	29.19
20-29 years	27.67	36.02	16.45	23.7
30-39 years	7.51	13.33	9.41	17.99
Av. hourly wage, Rbl (in 2019 prices)	176	167.9	207.4	237.7

[16] The data for the industry variable included in the model specification is available only starting from 2004.

N	6828	1838	2273	2991

Source: Authors' estimates using the RLMS-HSE data.

5. Does Wage Premium Rise with Experience?

In this section, we examine how earnings gains evolve over a worker's career. As we explained in more detail earlier, the stylized story goes as follows. An individual begins professional life with a low starting wage but, over time, through the gradual accumulation of productive skills through learning-by-doing and on-the job-training, progresses along the upward sloping wage curve. However, at a certain point in their career, wages may stagnate or even decline due to both external obsolescence and internal degradation, resulting in an inverted U-shaped curve. Wage profiles for individuals in different educational fields and occupations can vary, as STEM and non-STEM fields are differentially exposed to obsolescence and internal devaluation. Our hypotheses about how these differences depend on the college majors are presented in Section 4 above. We test these hypotheses below, first without using the APC decomposition.

a. Cross-Sectional Evidence

As Gimpelson and Zinchenko (2019) demonstrate, the wage gaps between STEM and non-STEM fields are statistically insignificant across the entire age spectrum. In this analysis, we utilize the data covering a longer period and an extended sample to re-estimate the Mincerian-type earnings equation, with potential labor market experience as a key regressor. In addition, in the next step, we include the regional institutional quality dummy. The estimated coefficients allow us to simulate wage-experience profiles, assuming other observables are held constant (see Figure 3).

$$ln(W_{it}) = \beta_0 + \sum_{e=1}^{E} \beta_{1e} D_{it}^{exp=e} + \beta_2 STEM_{it} + \sum_{e=1}^{E} \beta_{3e} D_{it}^{exp=e} \times STEM_{it} + \\ + \xi X_{it} + \theta_t + \varepsilon_{it}, i = 1, \ldots, N; \quad (1)$$

where W_{it} is the deflated hourly wage of individual i, who is observed at time t; D_{it}^{exp} is a vector of experience dummy variables; $STEM_{it}$ is an indicator variable that is equal to one if respondent i either has a STEM education at time t; vector X includes controls for marital status, urban/rural location, industry and region; θ_t represents year fixed effects and ε_{it} is an error term. The β_{3e} coefficients can be interpreted as the wage penalty or premium for STEM majors at any given work experience. We estimate equation (1) separately for men and women.

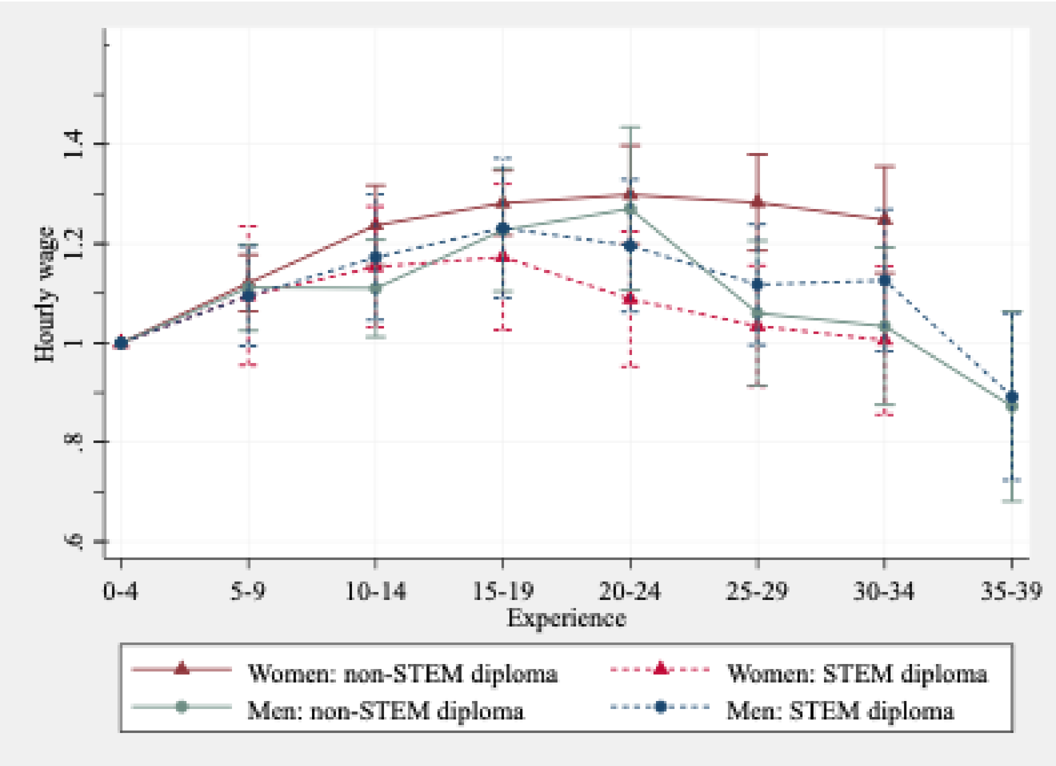

Fig. 3. Simulated wage profiles for STEM/non-STEM-educated workers. Wage in the group with 0-4 years of experience is taken as 1.

Source: Authors' estimates using the RLMS-HSE data.

These profiles exhibit several distinctive features common to both genders. They are relatively flat, have a low peak (typical for middle-income countries), and an early decline.[17] According to economic theory and multiple empirical studies, wages typically grow until late in one's career (Rubinstein & Weiss 2006). In our case, the premiums generated by experience are modest. Moreover, while STEM-educated workers tend to reach peak earnings earlier than their non-STEM counterparts, their wages also decline more sharply with experience. In contrast, non-STEM wage profiles decline more gradually in the latter half of the career. However, despite these visual differences between the wage profiles for STEM and non-STEM majors, these differences are not statistically significant for males but are significant at 1%-5% levels for females with 25-34 years of experience. These results remain robust across a range of specifications of equation (1), from the most conventional Mincer-type formulation to various combinations of controls used in our main model (available upon request).

[17] The wage profiles resemble those that have been repeatedly documented using different data sources for Russia (see Gimpelson & Zinchenko, 2019; Gimpelson, 2018; Aistov, 2018; Chernina & Gimpelson, 2023). One of the alternative sources is the Sample Survey of Population's Income and Participation in Social Programs conducted by Rosstat. In 2015, it asked respondents about their college majors. For the wage-experience profiles calculated using these data, see Appendix B Figure A1.

Contrary to our first hypothesis (H1), STEM-educated workers show no clear wage advantage over non-STEM peers. However, as the next section shows, these preliminary findings are due mainly to conflation of age/experience and cohort effects.

The impact of institutions. We now estimate the returns to experience using equation (2), which incorporates pairwise and triple interaction terms between experience, STEM/non-STEM major, and an institutional quality dummy, in addition to the main effects of these variables:

$$ln(W_{it}) = \beta_0 + \sum_{e=1}^{E} \beta_{1e} D_{it}^{exp=e} + \beta_2 STEM_{it} + \sum_{e=1}^{E} \beta_{3e} D_{it}^{exp=e} \times STEM_{it} + \beta_4 RI_i + \\ + \sum_{e=1}^{E} \beta_{5e} D_{it}^{exp=e} \times RI_i + \beta_6 STEM_{it} \times RI_i + \sum_{e=1}^{E} \beta_{7e} D_{it}^{exp=e} \times STEM_{it} \times RI_i + \\ + \xi X_{it} + \theta_t + \varepsilon_{it}, \qquad i = 1, \ldots, N; \tag{2}$$

where RI is an institutional quality index, which equals 1 if the Investment Risk Index exceeds the sample median (the region is classified as having weak institutions) and 0 if it falls below the median (the region is classified as having relatively strong institutions). The other variable names have the same meaning as in equation (1). Thus, this specification enables us to test Hypothesis 3. Estimation results are presented in Figure 4 and Table A1 (see Appendix).

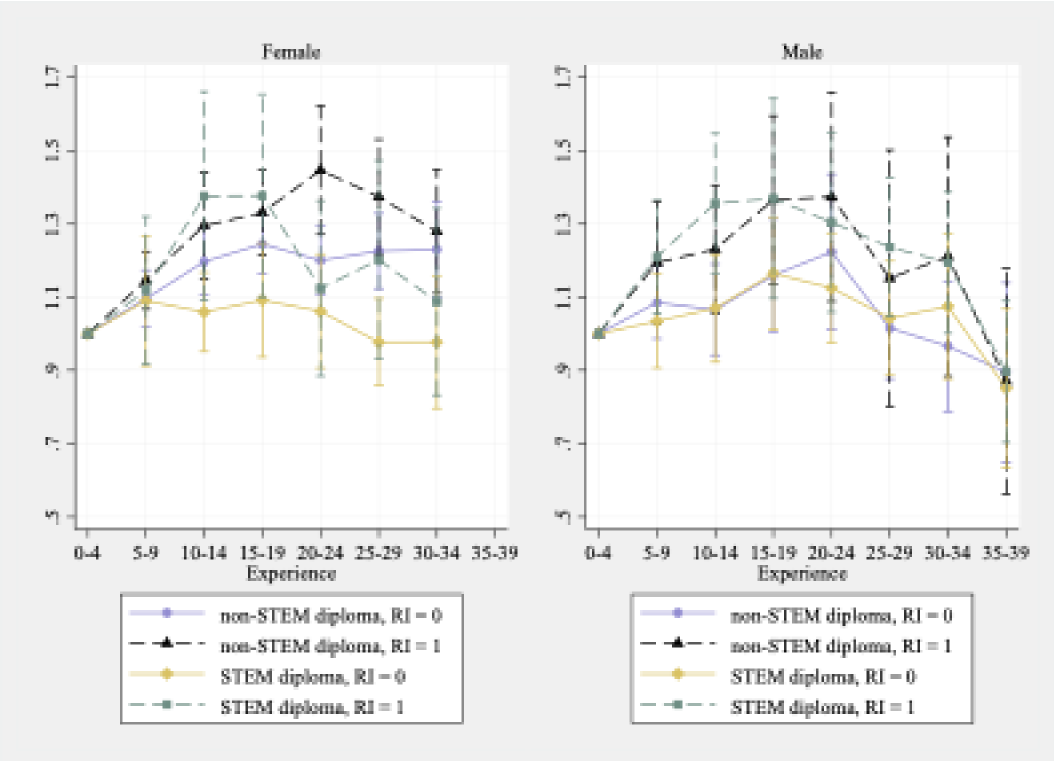

Fig. 4. Simulated wage profiles for female and male STEM/non-STEM-educated workers from regions with varying institutional quality. Wage in the group with 0-4 years of experience is taken as 1.

Source: Authors' estimates using the RLMS-HSE data.

The institutional quality does not appear to affect significantly either males with STEM/non-STEM diplomas or females. Consequently, our findings at this point do not provide empirical support for Hypothesis 3. Notice, however, that the baseline regression does not account separately for experience, period, and cohort effects because of perfect collinearity among these three variables. In other words, the cohort effect in this regression is combined with the effect of experience. This may contribute to the observed lack of statistical significance of the impact of institutional quality on the wage-experience profile.

b. Separating APC Effects

The collinearity of age/experience-period-cohort is referred to as the APC problem in the literature. Since our wage-experience profiles are derived from repeated cross-sectional data, they encompass both experience and cohort effects. Therefore, to accurately identify returns to experience in our study, we need to isolate cohort and time effects. The challenge of disentangling these three effects — age/experience, cohort, and time — is well-documented (for a survey see: Fosse & Winship, 2019). Given that APC variables form a perfect identity (P = A + C), there is no purely technical method to separate them. Additional identifying assumptions are required to estimate distinct effects.

Our objective here is to decompose the life cycle wage growth for STEM and non-STEM individuals into three distinct profiles for each group. It is important to note that these effects, being purely analytical constructs based on our assumptions, are not directly observable, regardless of the data available. Before explaining and applying the APC decomposition, we discuss the insights these effects can provide if properly separated.

Age/Experience Effect. Human capital accumulated through learning-by-doing or various job-related training programs is expected to boost productivity and, consequently, earnings. As individuals approach retirement, the potential gains from additional investment in human capital diminish, and skills may depreciate if not maintained. Under such conditions, labor productivity can stagnate or even decline, leading to a similar trajectory in wages. This incremental change in earnings due to additional experience, all else being equal, is referred to as the experience effect. Multiple studies have shown that the curve reflecting this effect rises monotonically but with diminishing returns to experience (Rubinstein & Weiss, 2006).[18]

Cohort Effect. It reflects inter-cohort differences in wage growth. In our case, cohorts are defined by the year of birth and are influenced by the socialization regime experienced during early adulthood (the formative period). This regime can have many cohort-specific features, such as the

[18] However, the results of these studies should be interpreted with caution as they did not employ APC decomposition.

type and style of education, labor market entry conditions, technology native to the cohort, values, etc. (see Oreopoulos et al., 2012; Schwandt & Von Wachter, 2020; Altonji et al., 2013; Kahn, 2010). Over time, shifts in demand can make cohort-specific human capital useless. Technological shocks can devalue previously acquired education and experience, but this impact can vary both across cohorts and within the STEM/non-STEM divide of the same cohort (Neuman & Weiss, 1995; Deming & Noray, 2020). The size of the cohort at entry also matters, as a larger cohort relative to the current demand can suppress educational premiums, flattening the life-cycle profile.

As a result, individuals of the same age group but belonging to different demographic cohorts (e.g., those in their 20s but born in the 1960s versus the 1990s) can differ significantly, even if other characteristics are similar. In developed countries, the cohort effect is usually small and of low statistical significance, while in countries experiencing prolonged systemic shocks, it can be more pronounced (Fang & Qiu, 2023; Chernina & Gimpelson, 2023).

In the Russian context, older generations entered the workforce during Soviet times, other cohorts did it during the recession years of the 1990s, and still others - during the economic boom at the beginning of the century. Guriev and Zhuravskaya (2009, p. 164) note that "Much of the value of the human capital stock accumulated during the command economy could have been wiped out by transition because it was comprised of skills specific to the planned economy and irrelevant for the market economy," although they did not test this theory explicitly. The cohort effect, when separated from other confounding factors, could serve as such a test. We conjecture that the devaluation of skill acquired in the Soviet time would be significantly greater for workers with non-STEM majors than those with STEM ones.

The time effect captures changes over time that are not specific to cohort or experience. Long-term economic growth is an example, as growth in aggregate productivity raises earnings for all, albeit to varying degrees. Such changes apply to all groups in employment, including different cohorts and age/experience groups.

Basic results.

To separate APC effects, we employ the decomposition methodology proposed by Lagakos et al. (2018), which is briefly outlined in Appendix B. Due to data constraints, the sample size is insufficient for using 5-year experience bins and, therefore, we use 10-year bins. Additionally, we apply a 10-year pre-retirement flat spot and consider two options for the depreciation rate: 0% and 1% per year.

Figures 5 and 6 present the decomposition results for STEM and non-STEM-educated males and females, respectively, assuming 0% depreciation rate.[19] The results are broadly similar for both genders, though the difference between STEM and non-STEM educated workers is more significant for females, particularly with respect to the wage-experience profile.

The left panel plots the wage-experience profiles assuming no human capital depreciation. The STEM wage profiles exhibit slower growth relative to non-STEM wages which grow monotonically until the pre-retirement plateau. Unlike simple cross-sectional framework, these profiles support our Hypothesis 1. Our point estimates indicate that while male and female non-STEM graduates as well as male STEM graduates achieve their peak earnings in the first 20-29 years of experience, the peak earnings for female non-STEM graduates occurs in the 10-19 years interval (see Table B1). In contrast, STEM graduates experience limited wage growth over their entire working life, with a 27% increase for males and 11% for females, primarily during the first decade of their careers and then plateaus.

Although the differences between the wage-experience profiles of STEM and non-STEM workers are not statistically significant at conventional levels for males, they are highly statistically significant for females. There are at least two reasons why the difference in experience profiles for STEM and non-STEM are so much more pronounced for females. Maume (1999) argued that females in male dominated fields tend not to move up the career ladder but are more likely to be pushed out. Also, STEM skills are largely developed early in careers and require continuous and costly updating, whereas non-STEM skills accumulate more gradually and depreciate more slowly (Deming, Noray 2020). We argue that women in Russia may often lack opportunities for updating their skills. As Russia is a relatively more male-dominated society, women are expected to have large amounts of housework in addition to their job responsibilities. Since non-STEM jobs typically require less intensive skill updating than STEM ones, women with non-STEM education experience less obsolescence of their skills. Also, because in many public sector jobs (such as education), on-the-job training is mandatory in Russia, women employed there are more likely to update their skills than those employed in STEM-related occupations.

In sum, these results broadly support our Hypothesis 1.

The right panels of Figures 5 and 6 illustrate the evolution of inter-cohort wage differences, which are a crucial aspect of our analysis. The cohort effects for males and females are quite similar. For non-STEM-educated workers, there are statistically significant wage disparities between the two

[19] We use APC decomposition for males and females based on separate samples for each gender because using the combined sample with a dummy variable for sex complicates the procedure significantly. Using the combined sample to estimate equations (1) and (2) generates qualitatively the same results.

oldest and four youngest cohorts for males and the three oldest and three youngest cohorts for females. The older cohorts are penalized compared to younger ones, with the difference between the point estimates for the youngest cohort (born after 1990) and the oldest cohort (born in 1940-1949) being approximately 60% for males and 50% for females. For STEM-educated workers, the cohort effect is smaller, non-linear, and mostly statistically insignificant. The most “successful” cohorts are those born in 1970-1979 for males and 1980-1989 for females, with the difference between the point estimates for these cohorts and the most penalized oldest cohort being 43% for males and 30% for females. For females, the wage profiles of STEM and non-STEM-educated workers are statistically significantly different, whereas for males, the differences are statistically significant only for the two oldest cohorts and for those born in 1970-1979. Notably, the shapes of the cohort effects are extremely robust and persist across alternative wage definitions.[20]

These cohort effects differ from the typical ones in advanced countries where cohort-specific human capital obsolescence is largely driven by technological change. Workers in occupations closer to the technological frontier have skills more exposed to external obsolescence, as can be captured by the cohort effect (Neuman & Weiss, 1995; Deming & Noray, 2020). Therefore, we might expect a stronger cohort effect for STEM than for non-STEM workers.

This contrasts with what we observe in the Russian data where the origin of cohort-specific obsolescence is different and more complex. The transition from a Soviet-type economy to markets radically altered the entire economic environment, causing mass destruction of old jobs, creation of new ones, large-scale labor reallocation from industry to services, and increased demand for business-related occupations. This deep structural transformation, that started in the early 1990s, brought about both organizational and technological changes. Previously accumulated human capital did not align with the demand of the market. Both STEM and non-STEM professionals who graduated before the transition faced significant adjustment costs, although the devaluation of skills was typically much more significant for those with non-STEM education.

For many non-STEM majors, especially those in social sciences and humanities, the transition resulted in an almost complete destruction of previously acquired skills because in these areas Soviet-type education was often highly distorted by ideological influences. Meanwhile, transition-induced organizational changes increased demand for specialists in management, logistics, finance, marketing, and commercial law. Soviet-era education did not provide these skills, which had to be developed from scratch. Consequently, the earnings of the older non-STEM cohorts have significantly lagged behind the earnings of the younger ones.

[20] As noted earlier, for the alternative definition, annual average wages are divided by *typical* working hours.

At the same time, natural science and engineering majors were more resilient to the transitional changes as their education was not tied to ideology. Mathematics, natural science, and engineering schools were relatively strong during the Soviet era and continued to educate competitive students during the transition. Unsurprisingly, the wage-cohort profile of STEM majors has been relatively flat implying that the older STEM-educated cohorts did not experience much greater devaluation of their skills than STEM graduates would experience due to technical progress in a relatively stable economy.[21] In short, the wage-cohort profile supports our Hypothesis 2.

The APC decomposition helps explain the somewhat counterintuitive results based on the simple cross-sectional analysis, which did not show any significant differences between STEM and non-STEM majors. The decomposition highlights two simultaneous processes that offset each other. The wage-experience profiles for STEM and non-STEM-educated workers rise monotonically although at different rates with the former lagging the latter. The trends for STEM and non-STEM cohorts, however, are the opposite, with the older non-STEM-educated workers in Russia being particularly disadvantaged because the two types of workers are differently exposed to external obsolescence. The non-STEM graduates from older cohorts face substantial losses because their human capital acquired in Soviet times has largely depreciated, while STEM skills have remained mostly relevant. As a result, the wage advantages gained by non-STEM majors through human capital accumulation over their careers (left panel) are largely offset by the losses experienced by cohorts that received their education during the Soviet era (right panel).

The middle panels of Figures 5 and 6 depict the time effect, reflecting recent macroeconomic developments. This effect is common across all cohorts and experience groups and is partially captured by GDP growth. Consequently, it is almost identical for STEM and non-STEM-educated workers. Since the start of the transition in 1992, the Russian GDP has followed a highly volatile trajectory, with a transformational recession in the 1990s followed by a boom in the 2000s. However, this period of rapid growth was succeeded by recessions and later stagnation. The GDP increased by 65% during 2000-2008 but only by 7% over the subsequent 12 years, according to Rosstat.

[21] Of course, transformational recession affected all cohorts as can be seen from the low level of wages in 2000 and a steep slope afterwards in the Year panel in the middle of Figures 5 and 6.

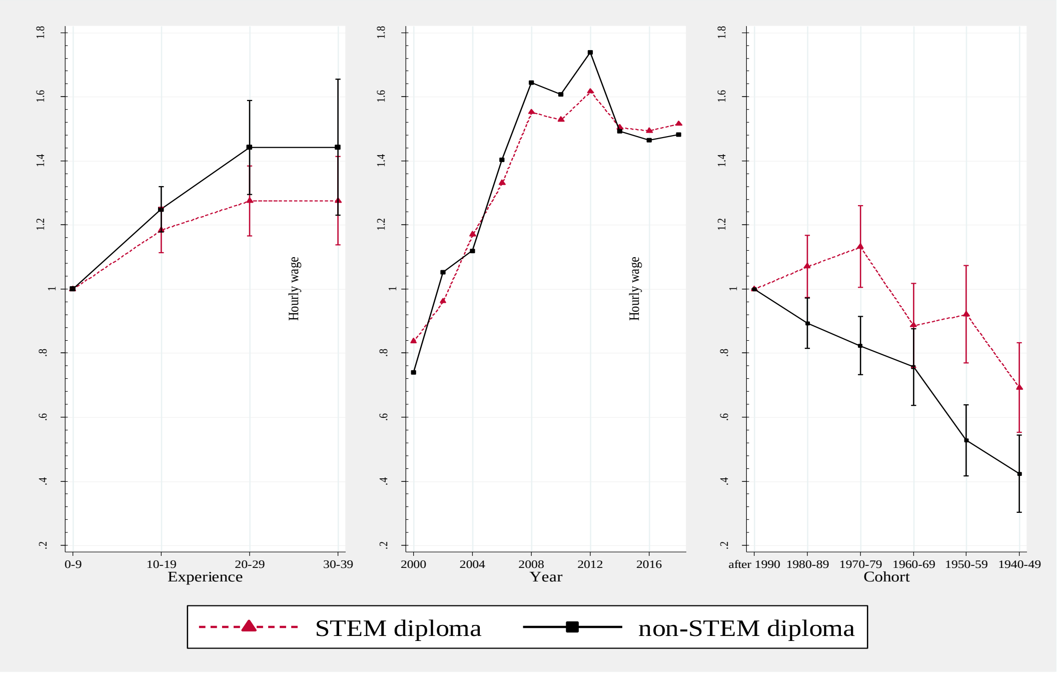

Fig. 5. Wage growth of STEM and non-STEM-educated workers due to experience, cohort, and year effects, males. The depreciation rate of human capital is 0%.

Source: authors' calculations using the RLMS-HSE data.

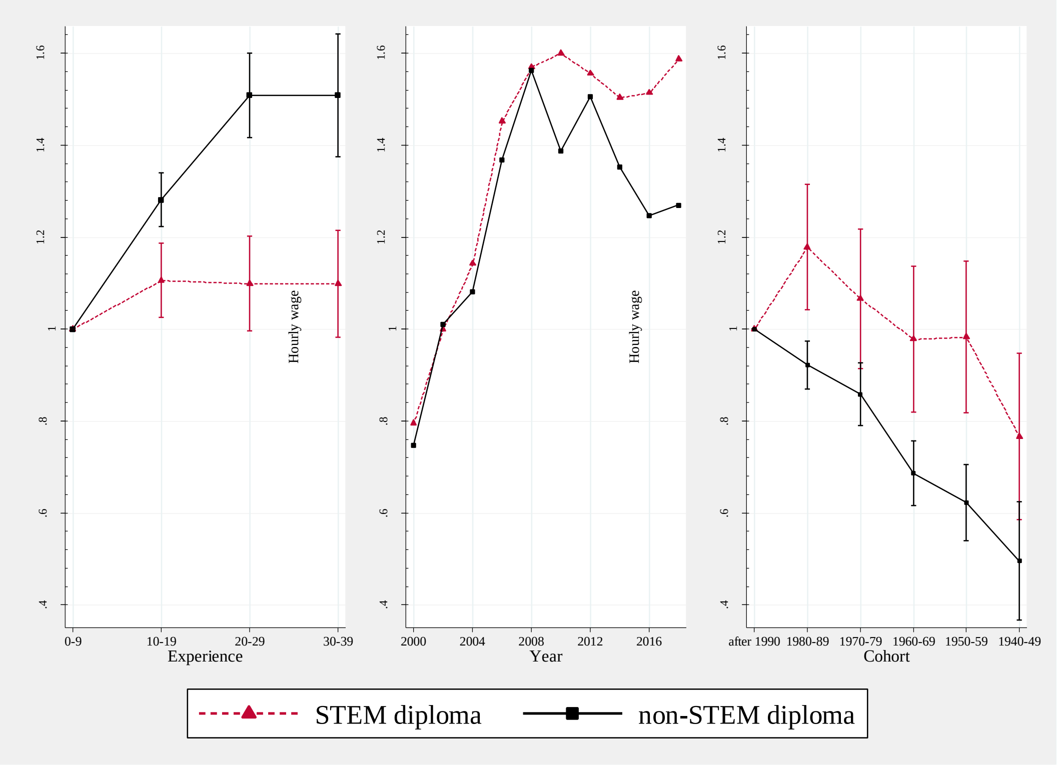

Fig. 6. Wage growth of STEM and non-STEM-educated workers due to experience, cohort, and year effects, females. The depreciation rate of human capital is 0%.

Source: authors' calculations using the RLMS-HSE data.

The impact of institutions. As we argued in the introduction, non-STEM-educated workers are more likely than STEM-educated ones to engage in rent-seeking activities as opposed to wealth creation. Therefore, according to our Hypothesis 3, we should observe steeper wage-experience profiles for non-STEM workers in the group of regions with weaker institutions. This is indeed what we find albeit only for males with less than 30 years of experience (see Figures 7 and 8). The absence of the difference in wage-experience profiles for older males is probably due to the fact that while most of them were educated in the USSR, the non-STEM education relevant to rent-seeking such as jurisprudence and public administration became much more popular only in post-Soviet times.

The results in Figure 7 also suggest that for younger Russian males, our Hypothesis 1 should be replaced with Hypothesis 3, because the entire difference in wage-experience profiles between STEM and non-STEM diploma holders for younger males are apparently driven by regions with relatively weak institutions while in institutionally stronger regions, there is virtually no difference between wage profiles for STEM and non-STEM-educated workers. One possible interpretation of this outcome is that the non-STEM diploma holders in the institutionally poor regions are more likely to work in occupations better suited to rent-seeking such as legal services and public administration or, more generally, occupations mostly involved in redistribution rather than value-creation. In contrast, the non-STEM diploma holders in the regions with relatively strong institutions are more likely to be involved in occupations in the "new" service economy such as management, market research, graphic design, and financial analysis. Similarly to STEM fields, these occupations experience relatively fast external and internal obsolescence.

The lack of the same pattern for females can be explained, as before, by the fact that in Russia, professions best suited for rent-seeking (such as the legal profession) are male-dominated.[22] Instead, females who hold non-STEM diplomas tend to work in the fields such as primary and secondary education, relatively low-level medical professions (nurses, general practitioners), librarians, and accountants. These fields do not present significant opportunities for rent-seeking while also not experiencing fast skill obsolescence. Therefore, we have the outcome consistent with Hypothesis 1 as pictured in Figure 8.

[22] In addition, rent-seeking opportunities in a male-dominated society are likely to be more accessible to men than to women, regardless of their field of education.

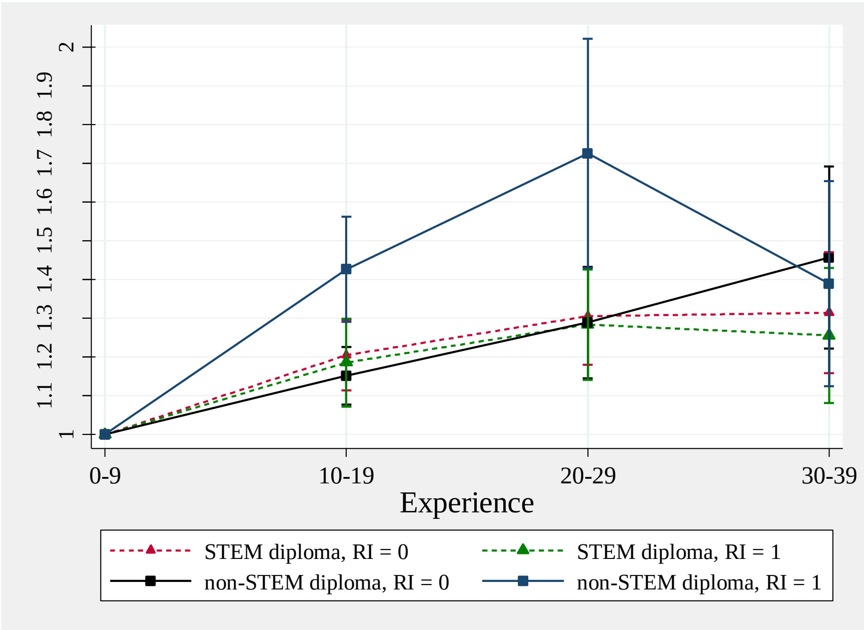

Fig. 7. Wage growth of STEM and non-STEM-educated workers due to experience in region with different institutional quality; males (RI=0 indicates relatively good institutions; RI=1 corresponds to relatively weak institutions). The depreciation rate of human capital is 0%.

Source: authors' calculations using the RLMS-HSE data.

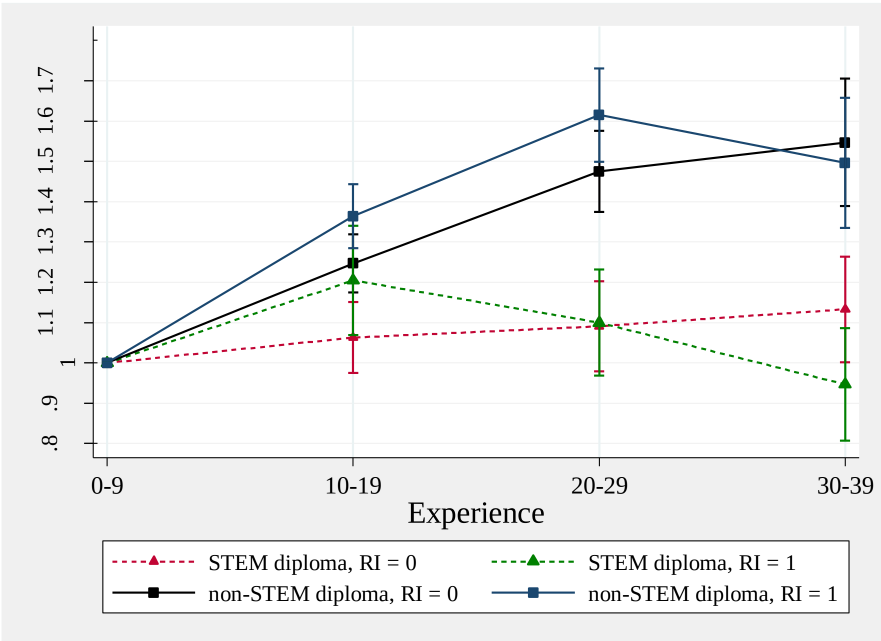

Fig. 8. Wage growth of STEM and non-STEM-educated workers due to experience in regions with different institutional quality; females (RI=0 indicates relatively good institutions; RI=1 corresponds to relatively weak institutions). The depreciation rate of human capital is 0%.

Source: authors' calculations using the RLMS-HSE data.

c. Robustness

Incorporating human capital depreciation during the final stage of working life reshapes wage profiles somewhat. Accounting for depreciation reallocates a portion of the wage change from the experience effect to the cohort effect, resulting in a flatter experience profile. However, this adjustment does not significantly alter the main differences between STEM and non-STEM profiles although some changes do occur. By introducing a 1% depreciation rate, we obtain the results depicted in Figures 9 and 10.

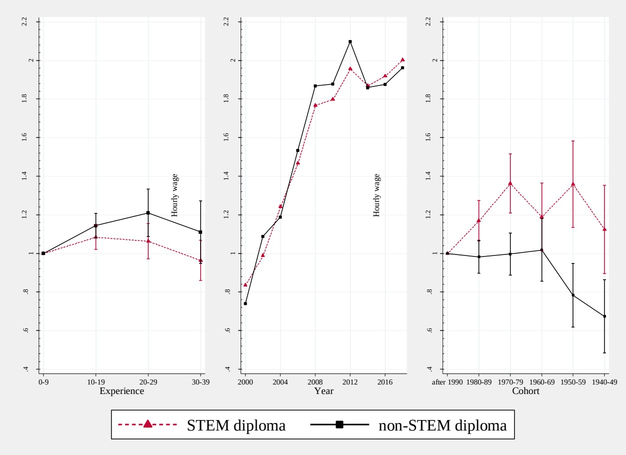

Fig. 9. Wage growth of STEM and non-STEM-educated workers due to experience, cohort, and year effects, males. The depreciation rate of human capital is 1%.

Source: authors' calculations using the RLMS-HSE data.

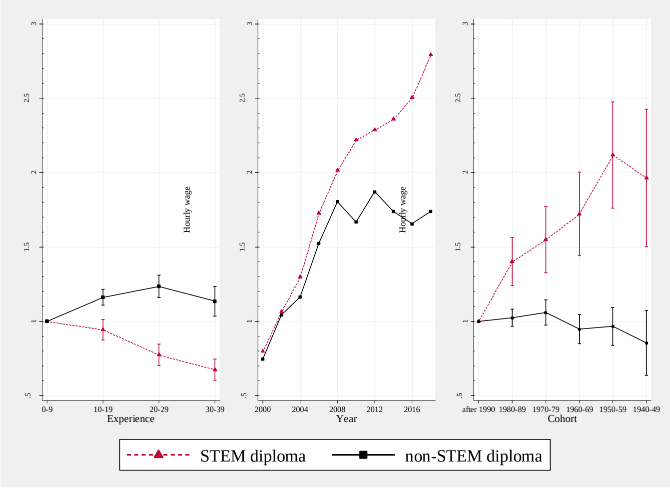

Fig. 10. Wage growth of STEM and non-STEM-educated workers due to experience, cohort, and year effects, females. The depreciation rate of human capital is 1%.

Source: authors' calculations using the RLMS-HSE data.

At the same time, the curve representing the experience effect is now significantly flatter compared to the one for the zero-depreciation scenario. While non-STEM graduates continue to accumulate human capital throughout their careers, the peak value has notably decreased. The trajectory for STEM graduates is less favorable, with minimal growth initially and a substantial decline towards the end of their careers.

As in the zero depreciation case, the inter-cohort differences are substantial and tend to offset the experience effect. The curve for the STEM cohort effect is significantly above that for non-STEM graduates, with particularly large differences for the older cohorts, indicating that STEM skills are considerably more resilient to Soviet times ideology than non-STEM skills.

With respect to the impact of institutional quality on wage-experience profiles, the trends remain qualitatively the same as in the case of zero depreciation rate (see Figures 11 and 12).

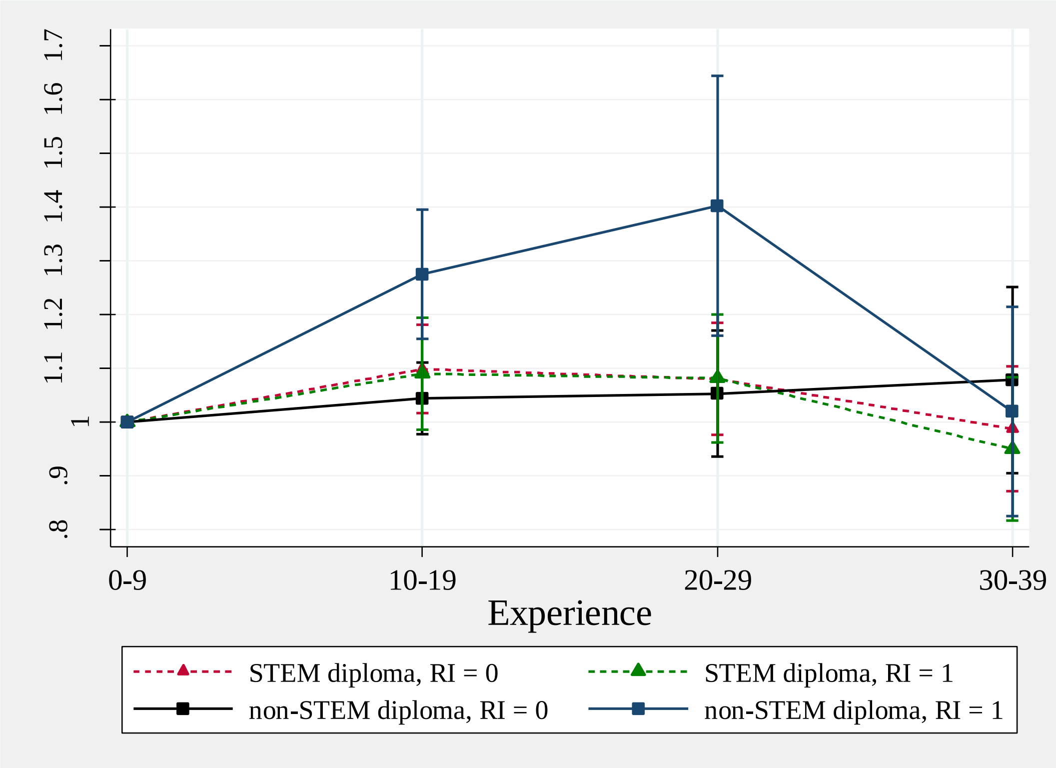

Fig. 11. Wage growth of STEM and non-STEM-educated workers due to experience in region with different institutional quality; males (RI=0 indicates relatively good institutions; RI=1 corresponds to relatively weak institutions). The depreciation rate of human capital is 1%.

Source: authors' calculations using the RLMS-HSE data.

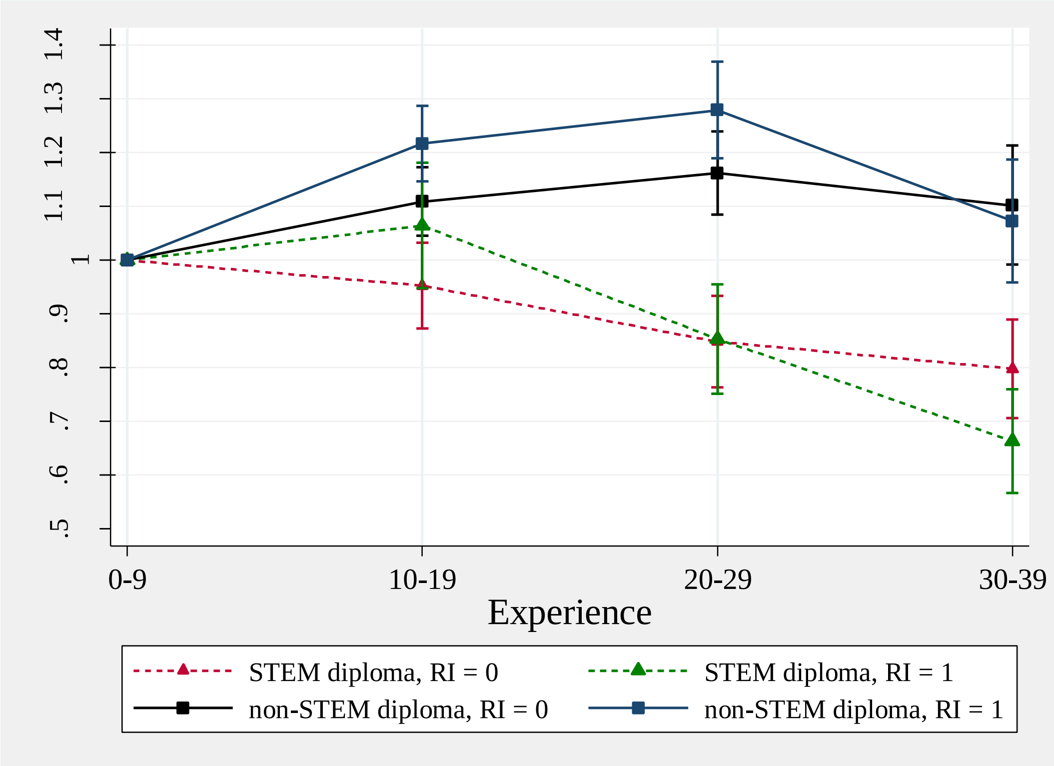

Fig. 11. Wage growth of STEM and non-STEM-educated workers due to experience in region with different institutional quality; females (RI=0 indicates relatively good institutions; RI=1 corresponds to relatively weak institutions). The depreciation rate of human capital is 1%.

Source: authors' calculations using the RLMS-HSE data.

6. Conclusions

We compare wage profiles for STEM-educated and non-STEM-educated individuals over their lifetimes in order to examine how the dynamics of these two types of human capital are affected by technological developments and institutional changes. To this end, we use novel applications of the Age-Period-Cohort (APC) effects decomposition to distinguish between STEM and non-STEM workers' life cycle wage growth and to account for heterogeneity in the impact of institutional environment on lifetime wage profiles.

Productive skills are crucial complements to technology. They are generated in the course of formal education and later are upgraded through on the job training and learning-by-doing. Skills acquired during formal education and early adulthood become outdated over years, creating a cohort effect for older cohorts. However, learning-by-doing accumulated during labor market experience can, to some extent, counteract these trends, although cognitive capacity and health tend to deteriorate with age, making retraining costly and the required "payback" period shorter. Thus, experience (correlated with aging) and cohort effects influence the stock of a person's skills, and they do not always move in the same direction. Although these challenges are relevant for any complex skills, STEM and non-STEM skills typically face different costs of obsolescence and upgrading. The evolution of wages over a working life reflects different trajectories of accumulation and depreciation of STEM and non-STEM human capital. Also, prolonged systemic shocks, such as transitions from a planned economy to a market economy and transformational recessions impact the existing human capital stock. The APC effects decomposition is complicated because these three effects are perfectly collinear. In order to disentangle them, we employ the procedure developed by Lagakos et al. (2018).

STEM and non-STEM human capital also differ in their productive utilization in different institutional environments. More able young people may select themselves into those fields and occupations which are expected to generate higher returns. In general, STEM activities are more likely to be wealth-creating, while some non-STEM activities are better suited to rent-seeking and, more generally, largely redistributive activities. In a better institutional environment, wealth-creating activities yield higher returns relative to rent-seeking ones, but under weaker institutions, the relationship is typically the opposite.

We develop hypotheses of how the above considerations are likely to affect lifetime wage profiles of holders of STEM and non-STEM degrees and test these hypotheses using a multiyear survey of workers in Russia. There are three important reasons for this choice. First, Russia aims to be a technologically developed country with a large STEM-related labor force. Second, the transition from a Soviet-type system to a market economy could have had a strong and negative impact on non-STEM human capital while having a relatively weaker effect on STEM skills, since mathematical and engineering education was free from ideology. This allows us to examine the differential cohort effect on holders of STEM and non-STEM diplomas which is typically negligible in economies that do not undergo deep ideological changes. Third, Russia's size and regional diversity provide an opportunity to explore the impact of the institutional environment on wage profiles of STEM vs. non-STEM graduates.

Our results illustrate how professional human capital ages in the Russian labor market. The cross-sectional wage-experience profiles for STEM and non-STEM professionals appear similar, but the underlying processes of skill accumulation differ. STEM specialists build up human capital slowly over their careers, while non-STEM professionals in older cohorts are penalized relative to their younger peers.

Applying the APC decomposition, we show interactions between the impacts of cohorts and experience that move wage profiles in opposite directions, offsetting each other. Wages tend to grow with experience, but STEM education is associated with flatter wage-experience profiles than non-STEM education, with the most pronounced differences observed among female workers. The cohort effect, apparently specific to the former Soviet-type economies, reveals itself in devaluing some types of older education, putting non-STEM cohorts educated during the Soviet period at a considerable disadvantage relative to those with STEM education acquired at the same time.

Importantly, in the Russian case, the age/experience effects act in the direction opposite to the cohort effects, rendering the cross-sectional analysis highly incomplete, if not simply misleading. Cross-sectional approach also hides the differential wage profiles between males and females. All these differences appear only under the APC decomposition, illustrating the need to apply this technique for the analysis of lifetime wage profiles, particularly in the economies undergoing deep structural changes. The APC decomposition is also necessary to understand properly the differences between wage profiles for STEM and non-STEM-educated individuals as well as the impact of institutional quality.

We also find that the quality of the institutional environment affects wage profiles of the holders of STEM and non-STEM diplomas. Wage-experience profiles for males with non-STEM education are considerably steeper in regions with weak institutions than in regions with stronger institutions, while institutional quality does not appear to impact STEM-educated males or females. The strength of these results is limited by the relatively small sample size and the lack of regional representativeness, but this line of inquiry deserves further and thorough examination. In addition, future research may involve more countries with better measured institutional heterogeneity across space and over time.

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Appendix A. Additional graphs and tables

The figures below present cross-sectional estimates of wage-experience profiles obtained from different data sets.

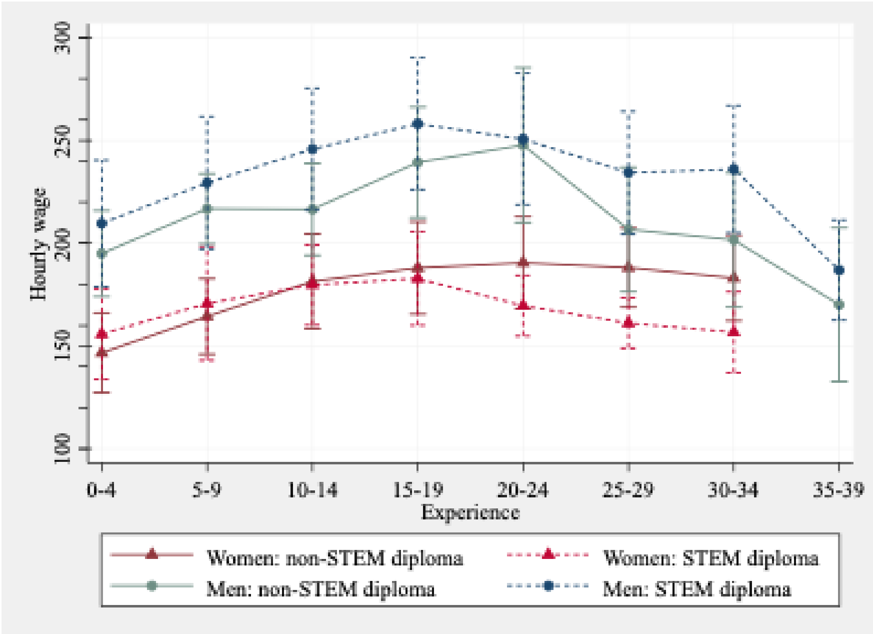

Fig. A1. Simulated wage profiles for STEM and non-STEM-educated workers.

Source: Authors' estimates using the RLMS-HSE data.

Note: The figure plots simulated wage profiles and 95% confidence intervals based on estimate of the eq (1).

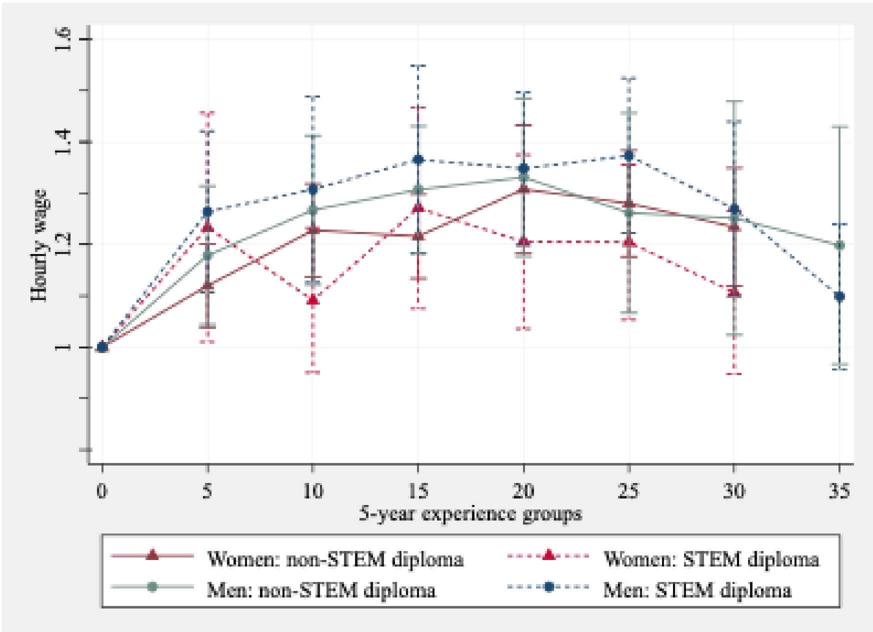

Fig. A2. Simulated wage profiles for STEM and non-STEM-educated workers. Wage in the group with 0-4 years of experience is taken as 1.

Source: Authors' estimates using the Sample Survey of Population's Income and Participation in Social Programs, 2015 year.

Note: The figure plots simulated wage profiles and 95% confidence intervals based on estimate of the eq (1).

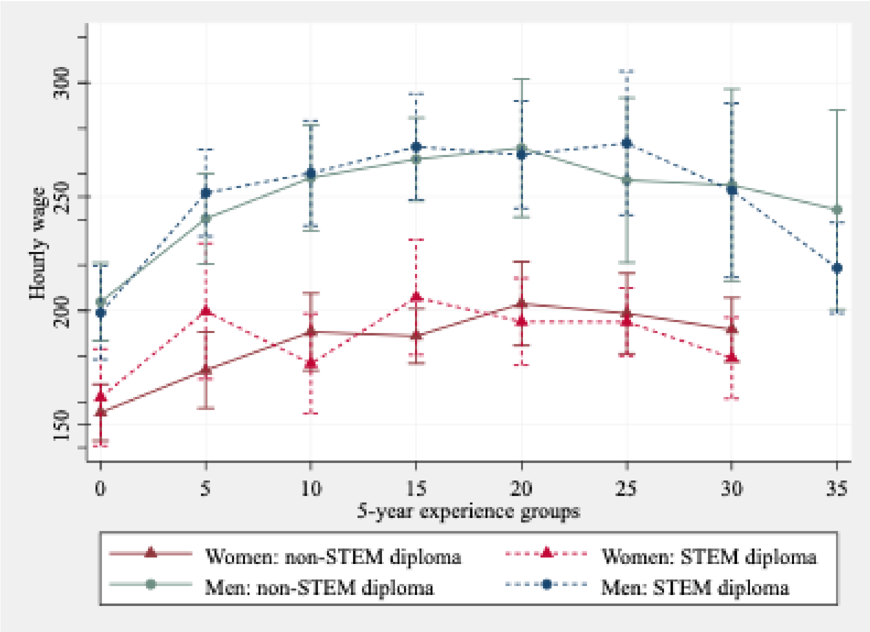

Fig. A3. Simulated wage profiles (in Rubles) for STEM and non-STEM-educated workers.

Source: Authors' estimates using the Sample Survey of Population's Income and Participation in Social Programs, 2015 year.

Note: The figure plots simulated wage profiles and 95% confidence intervals based on estimate of the eq (1).

Table A1. OLS Determinants of the Log of Hourly Wage, by Gender

Variables	Women		Men	
	b	S.E.	b	S.E.
Year (base = 2019)				
2004	-0.556***	0.051	-0.587***	0.066
2005	-0.415***	0.045	-0.414***	0.058
2006	-0.281***	0.049	-0.301***	0.063
2007	-0.179***	0.044	-0.251***	0.054
2008	-0.029	0.057	0.004	0.055
2009	-0.078	0.048	-0.114**	0.047
2010	-0.105**	0.049	-0.056	0.042
2011	-0.053	0.047	-0.061	0.041
2012	-0.011	0.037	0.025	0.036
2013	0.063**	0.032	0.057*	0.030
2014	0.021	0.038	-0.023	0.036
2015	-0.091***	0.030	-0.080**	0.032
2016	-0.074**	0.029	-0.079***	0.026
2017	-0.075***	0.022	-0.012	0.031
2018	-0.017	0.022	-0.005	0.024
Experience group (base = 0-4)				
5-9	0.091**	0.036	0.082*	0.047
10-14	0.180***	0.039	0.063	0.060

15-19	0.219***	0.033	0.148**	0.068
20-24	0.182***	0.040	0.202**	0.088
25-29	0.204***	0.043	0.016	0.070
30-34	0.207***	0.054	-0.035	0.094
35-39			-0.111	0.140
STEM diploma (= 1)	0.062	0.057	0.121	0.079
Interaction term: Experience group # STEM diploma				
5-9 (= 1) # STEM diploma (= 1)	-0.005	0.089	-0.048	0.073
10-14 (= 1) # STEM diploma (= 1)	-0.122	0.075	0.004	0.094
15-19 (= 1) # STEM diploma (= 1)	-0.132	0.082	0.004	0.099
20-24 (= 1) # STEM diploma (= 1)	-0.123	0.082	-0.084	0.100
25-29 (= 1) # STEM diploma (= 1)	-0.227***	0.047	0.026	0.074
30-34 (= 1) # STEM diploma (= 1)	-0.230**	0.095	0.106	0.109
35-39 (= 1) # STEM diploma (= 1)			-0.050	0.184
Investment risk index: RI (= 1)	-0.165**	0.075	-0.157	0.107
Interaction term: Experience group # RI				
5-9 (= 1) # RI (= 1)	0.045	0.050	0.096	0.086
10-14 (= 1) # RI (= 1)	0.079	0.070	0.145	0.096
15-19 (= 1) # RI (= 1)	0.067	0.057	0.163	0.110
20-24 (= 1) # RI (= 1)	0.187***	0.072	0.116	0.139
25-29 (= 1) # RI (= 1)	0.114	0.071	0.126	0.171
30-34 (= 1) # RI (= 1)	0.039	0.084	0.226	0.164
35-39 (= 1) # RI (= 1)			-0.027	0.233
Interaction term: STEM diploma # RI				
STEM diploma (= 1) # RI (= 1)	-0.061	0.124	-0.114	0.105
Interaction term: Experience group # STEM diploma # RI				
5-9 (= 1) # STEM diploma (= 1) # RI (= 1)	-0.019	0.148	0.061	0.098
10-14 (= 1) # STEM diploma (= 1) # RI (= 1)	0.183	0.163	0.093	0.115
15-19 (= 1) # STEM diploma (= 1) # RI (= 1)	0.166	0.148	-0.002	0.145
20-24 (= 1) # STEM diploma (= 1) # RI (= 1)	-0.130	0.145	0.032	0.149
25-29 (= 1) # STEM diploma (= 1) # RI (= 1)	0.093	0.134	0.045	0.173
30-34 (= 1) # STEM diploma (=1) # RI (=1)	0.068	0.185	-0.120	0.177
35-39 (= 1) # STEM diploma (=1) # RI (=1)			0.080	0.276
Married (=1)	-0.007	0.020	0.140***	0.026
City (= 1)	0.150**	0.073	0.221***	0.070
Federal district (base = Central)				
Northwestern	0.196	0.128	0.181	0.121
Southern	-0.232**	0.106	-0.221***	0.082
Volga	-0.131	0.097	-0.118	0.072
Ural	-0.083	0.129	0.031	0.085
Siberian	-0.137	0.098	-0.175**	0.081
Far Eastern	-0.080	0.138	-0.013	0.111
Industry group (base = Agriculture)				
Industry (manufacturing + mining)	0.265*	0.152	0.281**	0.122
Construction	0.390**	0.165	0.267**	0.120
Market services	0.238	0.150	0.261**	0.126
Non-market services	0.106	0.149	0.114	0.121
Other	0.358**	0.151	0.189	0.161
const	4.747***	0.206	4.782***	0.178
N	8616		5203	

Source: Authors' estimates using the RLMS-HSE data.
Note: Estimates are based on pooled data for 2004-2019 years. Each row in the table represents the coefficient and its standard error from regression (2). Standard errors are clustered by regions. $* p<0.10$, $** p<0.05$, $*** p<0.01$.

Appendix B. APC decomposition[23]

The association between wages and APC effects can be modeled using a modified Mincer-type equation (B1):

$$ln(W_{ict}) = \alpha + \sum_{e=1}^{E} \theta_e D_{ict}^{exp=e} + \sum_{l=1}^{L} \delta_l educ_{ict}^{l} + \gamma_t + \lambda_c + \varepsilon_{ict}, \quad i = 1, \dots, N; \quad \text{(B1)}$$

where W_{ict} represents the hourly wage of individual i from cohort c in period t; D_{ict}^{exp} denotes 10-year experience bins, $e = 1, \dots, E$; $educ_{ict}^{l}$ indicates education level, $l = 1, \dots, L$; γ_t – period dummies; λ_c – cohort dummies; ε_{ict} is the random error.

To address APC collinearity in equation (B1), additional constraining assumptions are required. Our study relies on Human Capital Theory (HCT) and its implications concerning investments in human capital over the life cycle (Ben-Porath, 1967). We apply the approach first suggested by Heckman et al. (1998) and later empirically realized by Lagakos et al. (2018). This approach uses the intuition that new human capital investments during the final pre-retirement period are practically absent, rendering the experience effect almost negligible. This period, often referred to as the "flat spot," typically lasts 5 or 10 years. By following the same pre-retirement group over the flat spot period, the age/experience effect is assumed to be zero, while the cohort effect is absent by design. This leaves the total observed wage growth to be explained by the time effect and depreciation, *(d)*. The size of *d*, following Lagakos et al. (2018), is assumed to be 0% or 1%. It is important to note, that no investments and zero depreciation can be also understood as non-zero investments equal in absolute value to non-zero depreciation. Depreciation equal to 1% represents the situation when the lack of new investments halts human capital accumulation, and the stock of human capital shrinks due to depreciation. Consequently, the residual wage growth, purged of the time effect, is divided between age/experience and cohort effects.

More formally, the time trend of wage growth, (g_M), is equal to the sum of two components. The first component is the time effect, (g_γ), which represents wage growth due to productivity growth and capital accumulation common to all cohorts. The second component is g_λ, which represents productivity growth due to changes in labor force cohort composition. Each cohort has its own productivity, thus general productivity changes when older cohorts leave the labor force and new

[23] This Section is based on (Chernina & Gimpelson, 2023).

cohorts enter. As discussed earlier, we can infer g_γ from g_y, the wage growth in the last y years of a career, and the depreciation rate d. Thus, equation (B2) must hold:

$$g_M = d + g_y + g_\lambda \tag{B2}$$

The estimation procedure, borrowed from Lagakos et al. (2018), proceeds as follows. First, we estimate the time trend of wage growth, g_M. Initially, the entire value of the time trend is attributed to the time effect, g_γ. Wages are deflated using the time trend, and then equation (B3) is estimated:

$$ln(W_{ict}^d) = \alpha + \sum_{e=1}^{E} \theta_e D_{ict}^{exp=e} + \sum_{l=1}^{L} \delta_l educ_{ict}^l + \gamma_t^* + \lambda_c + \varepsilon_{ict}, \qquad i = 1, \dots, N; \tag{B3}$$

where W_{ict}^d is the deflated wage of individual i from cohort c in period t; D_{ict}^{exp} − 10-year experience bins, $e = 1, \dots, E$; $educ_{ict}^l$ − education level, $l = 1, \dots, L$; γ_t^* − modified period dummies, such that $\frac{1}{T}\sum_{t=0}^{T} \gamma_t^* = 0$, these time period dummies would show deviations from the time trend; λ_c – cohort dummies; ε_{ict} is the random error term.

Equality (B2) is checked with the estimated values of g_M, g_y and g_λ, given the assumed value of d. The procedure continues with updated value of g_M until equality (B2) is satisfied.

Table B1. Estimated Parameters of Experience Wage Profile

Depreciation, Characteristics	**Peak Experience, Years**	**Peak Height**	**95% CI**
d=0%, STEM, males	20-29	1.27	(1.17; 1.39)
d=0%, non-STEM, males	20-29	1.44	(1.31; 1.58)
d=0%, STEM, females	10-19	1.11	(1.02; 1.20)
d=0%, non-STEM, females	20-29	1.51	(1.44; 1.58)
d=1%, STEM, males	10-19	1.08	(1.02; 1.15)
d=1%, non-STEM, males	20-29	1.18	(1.07; 1.29)
d=1%, STEM, females	0-9	1.00	(1.00; 1.00)
d=1%, non-STEM, females	20-29	1.19	(1.14; 1.25)

Source: Authors' estimates using the RLMS-HSE data.

Note: The table contains coefficients and 95% confidence intervals from estimates of the equation (B3).