HUMAN CAPITAL PRODUCTIVITY IN RUSSIAN ECONOMY IN THE CONTEXT OF TECHNOLOGICAL REGRESSION

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Abstract

Recent research has shown a growing interest in understanding the effects of geo-economic fragmentation in the post-pandemic era, combined with ongoing geopolitical tensions. This article aims to evaluate structural changes in the productivity of human capital in Russia during the period from 2017 to 2022 and their impact on national technological regression. Methods include Mincer function analysis and adapted Fagerberg's accounting for structural change in human capital productivity. Recent data from RLMS-HSE and Rosstat quarterly microdata are used to analyse human capital and value added across 19 sectors. Findings reveal a concerning trend: the total economic growth rate is 6,8% over the studied period, while change in human capital productivity is even lower, having increased by a mere 5,1%. This gap underscores significant stagnation and depreciation of human capital. Several factors contribute to this pattern, including economic shocks from the pandemic and sanctions, ageing of the population, shortage of skilled labour due to migration in 2022, and reduced access to foreign technologies. The manufacturing sector contributes only 1% to the overall increase in human capital productivity. In summary, recent geopolitical decisions have had negative effects on human capital, resulting in technological regression.

Key words: human capital, productivity, structural change, economic fragmentation, technology regression, Russia.

JEL Codes: J24, E24, O33

Introduction

Recent global events increased research interest in the phenomena of economic and geopolitical fragmentation, as observed by Campos et al. (2023). In recent years, emergence of political populism and disparities in national interests have contributed to escalating geopolitical tensions and deglobalization. Sanctions have emerged as an alternative to military actions, which often yield catastrophic consequences. The increase in sanctions disrupted supply chains that provided technologies to some developing nations in recent years. The reallocation of economic growth resources entails not only short-term productivity losses, but also dynamic inefficiencies in the diffusion of knowledge across different sectors of the global production system (Góes & Bekkers, 2022). Changes in the supply chains are projected to decrease welfare losses of up to 12% in specific regions, impacting the accessibility of production and socially significant technologies, diminishing the rate of human development.

In the context described above, human capital, which serves as a stock of knowledge and competencies necessary for individual performance, finds itself in conditions of high uncertainty. In the period from 2014 to the present, the Russian labor market was exposed to the sanctions, but until recently it managed to adapt to previous shocks (Zubarevich, 2022). Notably, despite the presence of limited transparency, opportunistic employer behavior, and imperfect legislative regulation, the Russian labor market has showed remarkable flexibility and adaptability (Gimpelson & Kapeliushnikov, 2013). Over the long term, this resilience has contributed to a decline in trust among employees towards their employers and has resulted in diminished labor mobility among older segments of the workforce. Unlike previous periods, sanctions pressure directly affected education and high value-added industries, limiting their direct access to new technologies. Consequently, the development models have shifted from entrepreneurial and competitive paradigms towards hierarchical and clan-based values, increasing the risks of stagnation and loss of accumulated human capital (Gimpelson, 2022). A critical objective is the assessment of potential losses in value-added attributed to the inefficient utilization of human capital.

The purpose of this article is to evaluate structural changes in the productivity of human capital and their impact on technological regression. Structural changes involve the redistribution of labor and accumulated human capital between different sectors, distinguished by the level of technology and added value. Unlike previous studies, instead of relying on the conventional metric of man-hours worked, the study employs the metric of human capital accumulation for each individual, measured as educational attainment and work experience.

1 Literature review

This study follows the neoclassical view of human capital, suggesting that human capital represents the stock of labor market-relevant professional knowledge and competencies that support value-added processes (Becker, 1993). Previous studies have shown that human capital is very sensitive to technological changes, macroeconomic shocks and institutional changes that directly or indirectly affect the demand and supply of qualified labor, educational strategies of the population and the structural content of the competencies and skills of those employed in the labor market (Alexeev, 2023; Gimpelson & Kapeliushnikov, 2013). Specifically for Russia, these consequences were compounded by two waves of sanctions in 2014 and 2022, which affected not only trade flows and consumer price growth, but also significantly changed access to foreign technologies, stimulating the ineffective strategies of import substitution.

Russia's integration into international supply chains over the past three decades has resulted in massive imports of technology to bridge the gaps stemming from the Soviet era (Dabrowski, 2023). First of all, this primarily targeted socially significant technologies that support the consumer sector, as well as production technologies that supported the export of raw materials. Technologically regressive imports has impacted on national innovative system fragmentation, primarily focusing efforts on supporting specialized projects (Zubarevich, 2022). In turn, this affects the development of the education system and scientific research, knowledge exchange and structural capital in the form of technology and know-how. In this context, the growth rate of real wages decreased, corresponding to the growth rate of labor productivity, and labor in the manufacturing sector continues to rapidly become cheaper, reaching a historical minimum in 2023 (Kapeliushnikov, 2023). The long-term decline of the manufacturing sector could further widen the technology gap. Prevailing institutional equilibrium in the atypical Russian model of the labor market in the long term is undermined by the demographic crisis (Kapeliushnikov, 2023).

Crisis in the domestic labor market affects distribution of labor between economic sectors (Dabrowski, 2023; Kapeliushnikov, 2023). Over a long period of time, structural transformation has been associated with a redistribution of labor from the primary to the secondary and then to the tertiary sector (Fagerberg, 2000). Structural changes are characteristic of the labor market with the redistribution of labor with different qualifications in a shorter transition period (Alexeev, 2023). Historically, in Russia, these changes over the past three decades were primarily driven by the transition to the market-based model of the economy, with an increasing demand for economic and financial specialties. However, during the recent wave of sanctions, structural changes are expected to be more closely associated with competencies in the high-tech sector. Thus, based on a brief review of the literature, the author formulates research questions:

1. How does the structure and productivity of accumulated human capital stock in the economy change in the context of geopolitical fragmentation?

2. How might changes in human capital productivity impact on technological regression?

2 Data and methods

In the study, the author first evaluates changes in human capital in the period from 2017 to 2022 based on data from the Russian Longitudinal Monitoring Survey - Higher School of Economics (*The Russia Longitudinal Monitoring Survey - Higher School of Economics (RLMS-HSE)*, 2022), and then determine structural changes in human capital productivity based on quarterly microdata from Rosstat (*Labor Resources, Employment and Unemployment. Microdata for 2017-2022*, 2023). First of all, the parameters of Mincer equation are estimated with control variables reflecting employment conditions, gender, and regional institutional differences to conclude on changes in the returns to human capital.

The study subsequently evaluates structural changes in productivity driven by the dynamics of the redistribution of accumulated education and work experience. Changes are estimated using the model proposed by Fagerberg (2000), which decomposes the productivity index over a period into three components. However, to measure the volume of labor in the labor market, this study uses its qualitative characteristic, the sum of accumulated man-years of education and production experience for each period and each industry, while the original model uses a number of man-hours. To calculate the total relevant human capital *RHC* in the form of relevant man-years of training (*RS*) and potential experience (*EX*) in industry *j* for the number of employed population *N* in period *t*, the quarterly weight *w* of respondent *i* in the representative sample of Rosstat is used. To calculate the number of years of relevant education, the total compulsory number of years of education *S* and the number of years of vocational education *PE*, multiplied by the coefficient μ, are used:

$$RHC_{jt} = \sum_{i=1}^{I} w_{it} RS_{it} + \sum_{i=1}^{I} w_{it} EX_{it} = \sum_{i=1}^{I} w_{it} (S_{it} + \mu PE_{it}) + \sum_{i=1}^{I} w_{it} EX_{it_j} \quad (1)$$

The coefficient μ is equal to 1 if the respondent noted that his vocational education fully or mainly corresponds to his current job and zero if the acquired professional education is not relevant for the current job. Human capital productivity (*HCP*) is calculated as the ratio of value-added *VA* to the total supply of quality labor (human capital), modified by man-years of accumulated relevant education and experience *RHC*. The supply of man-years is limited and distributed across industries. The result is a modified version of Fagerberg's (2000) shift-share decomposition model. The share of the consumed *RHC* resource in each sector is denoted by d_j. The model contains three components of *HCK*, meaning of which will be explained using an example in the results section:

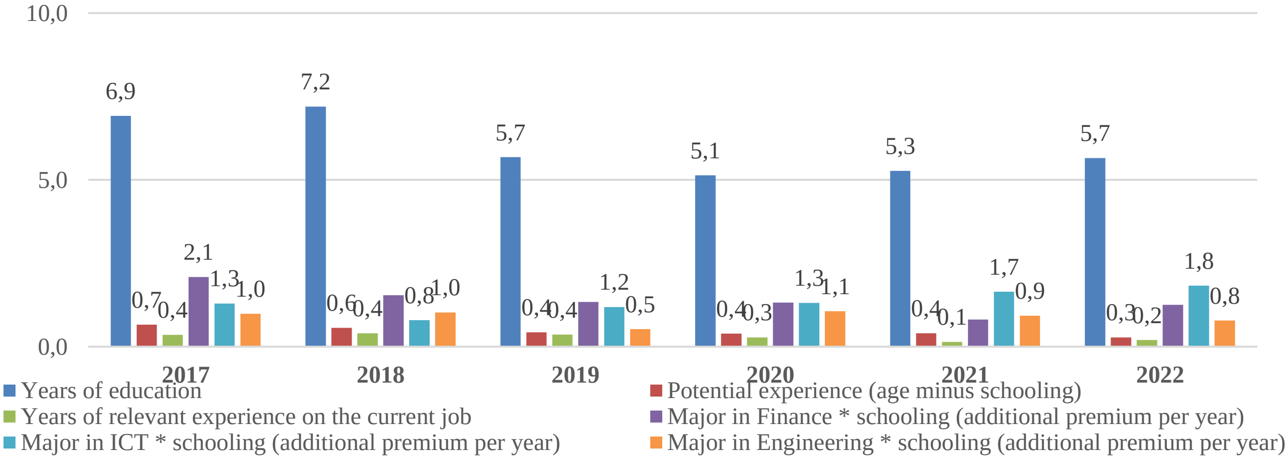
$$HCP_t = \frac{VA}{RHC} = \frac{\sum_{j=1}^{J} VA}{\sum_{j=1}^{J} RHC_j} = \sum_{j=1}^{J} \left(\frac{VA_j}{RHC_j} \frac{RHC_j}{\sum_{j=1}^{J} RHC_j} \right) = \sum_{j=1}^{J} \left(HCP_{jt} \times d_{jt} \right) \quad (2)$$

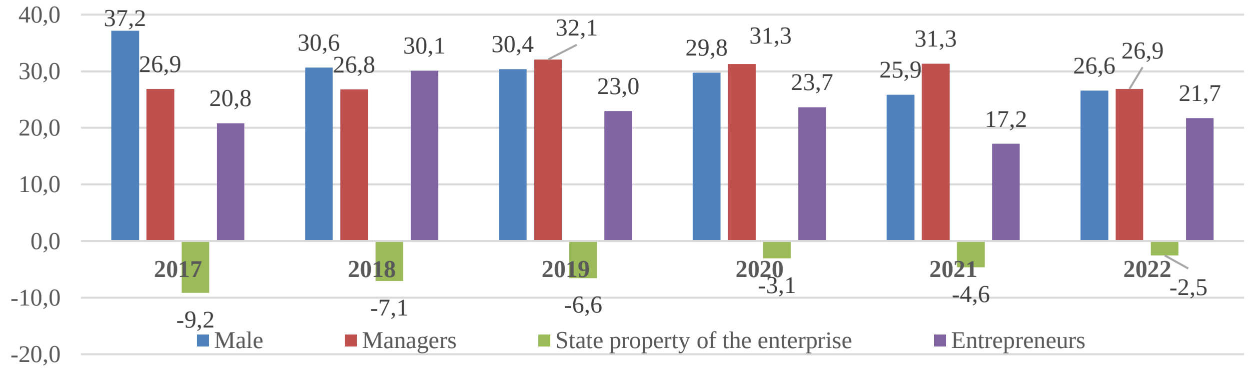
$$\frac{\Delta HCP}{HCP_t} = \sum_{j=1}^{J} \left(\frac{HCP_{jt}(d_{j(t+1)} - d_{jt})}{HCP_t} + \frac{(HCP_{j(t+1)} - HCP_{jt})(d_{j(t+1)} - d_{jt})}{HCP_t} + \frac{(HCP_{j(t+1)} - HCP_{jt})d_{jt}}{HCP_t} \right) = \sum_{j=1}^{J} HCK_{1j} + HCK_{2j} + HCK_{3j} \qquad (3)$$

3 Results and discussion

An assessment of the parameters of Mincer equation showed that Russian human capital during the period under review did not undergo significant changes in terms of the return on each component of accumulated experience, education and other characteristics (Figure 1).

Fig. 1: Percentage increase in earnings for each component of human capital (top chart) and other factors measured by dummy variables (bottom chart) in 2017-2022. All coefficients are significant at the level < 1%, and < 5% for years of relevant experience.



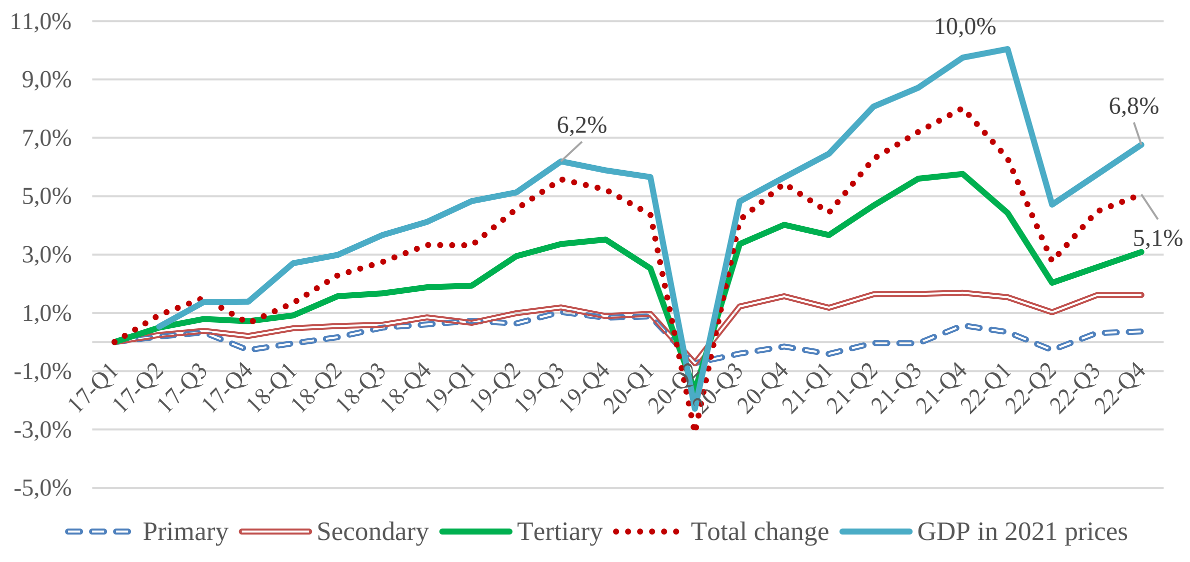


Source: Obtained by the author using RLMS-HSE 2022 update

The return on education has remained relatively steady at around 6-7% per year of education acquired. Notably, graduates specializing in information and communication technology (ICT), finance, and engineering fields have experienced higher returns on their competencies, with additional earnings potential ranging from 0,8% to 1,8% per year of education. These return patterns showed minimal fluctuations in 2022. More substantial increases in earnings were driven by gender and occupational statuses. Men, on average, earned 25-35% more than their female counterparts. A similar earnings differential was observed among individuals holding managerial positions. Traditionally in the Russian labor market, employees of state-owned enterprises earned 2-10% less than those in non-state-owned companies. However, it's worth noting that in 2022, this income gap narrowed significantly.

Given the absence of significant changes in the structure of returns from various components of human capital, the total stock of human capital for each industry is calculated using Formula (1). Subsequently, three groups of structural indicators are computed using Formula (2). The results of calculating the overall change in returns are depicted in Figure 2, where all growth rates are relative to a single period—the first quarter of 2017, which is designated as 100%. The indicator chosen is the value-added by industries at 2021 prices, with the exclusion of seasonality. Additionally, for comparative purposes, the GDP growth rate for the specified period has been included.

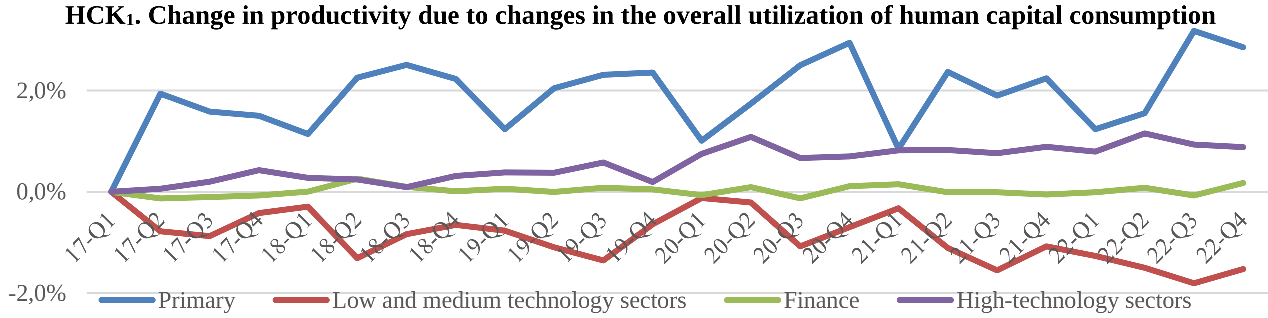
Fig.2: Overall changes in human capital productivity ($\frac{\Delta HCPt}{HCP_{2017}}$) between sectors and GDP growth compared to the first quarter of 2017.

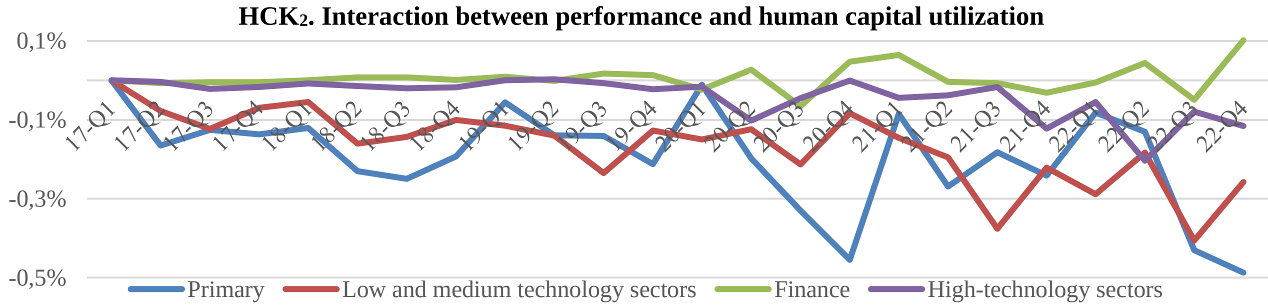


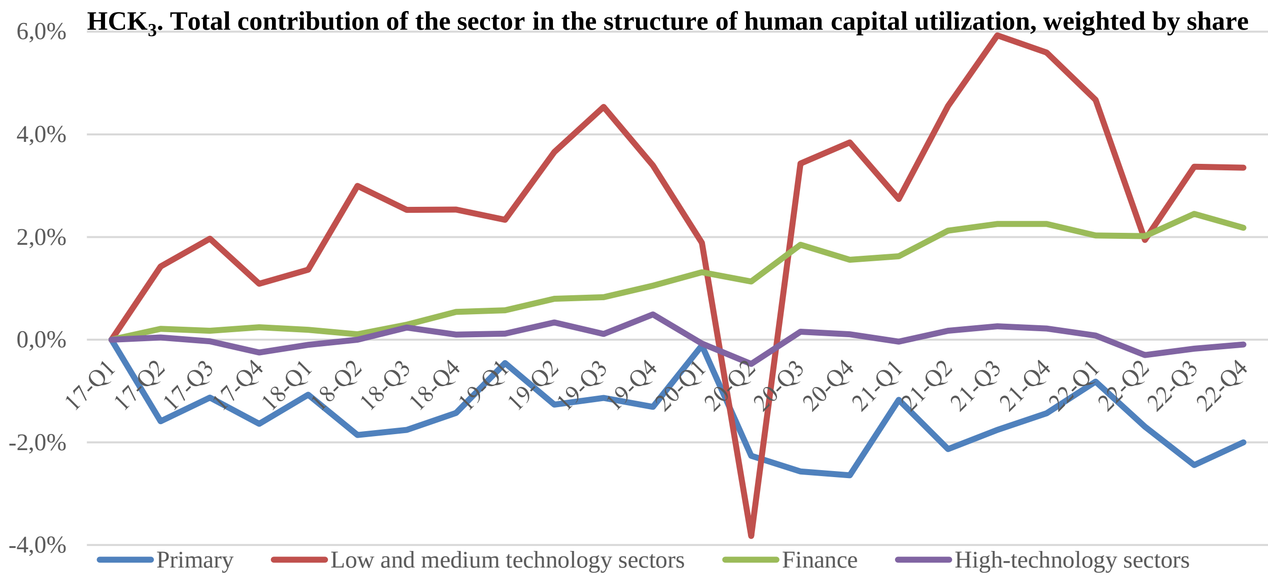
Source: Calculated by the author based on Rosstat data.

Figure 2 illustrates a clear correlation between changes in human capital productivity and the in GDP. However, starting in 2021, a consistent gap of 2-3% emerges between them, suggesting a declining return on each unit of accumulated human capital. The sectors with the largest accumulated person-years of education predominantly align with the employment structure. Over the 2017-2022 period, the average age of individuals employed in these sectors increased by 3% and 4%, respectively, reaching 42,6 and 40,2 years. The aging of the employed population in the labor market has led to a rise in expected work experience, while the overall educational structure has remained relatively constant. Due to constraints on the skilled labor in the labor market, coupled with an overall unemployment rate of 1% in certain regions as of June 2023, there has been a notable shift in the composition of the employed population. The number of employed individuals in the age group of 30 to 49 has increased by 4 percentage points within the overall structure, whereas employed youth aged 20 to 29 have decreased by 5,6 percentage points. In light of these dynamics, the findings align with the assumptions articulated in Kapeliushnikov (2023) for the 2011-2021 period. Subsequently, a decomposition of the overall change in human capital by industry is conducted (Figure 3).

Fig. 3: Decomposition of the human capital productivity change between industries in accordance with Formula (3).







Source: Author's calculations based on Rosstat data

The first component (HCK_1) includes the increase in human capital productivity from its reallocation across industries. A higher value of this indicator signifies a greater proportion of highly productive industries integrating accumulated human capital into the overall employment structure. The most pronounced changes in HCK_1 are evident in the primary mining and agriculture, where shifts in the utilization of human capital have occurred. Meanwhile, the efficiency of human capital utilization in the finance and high-tech sectors has remained relatively stable. There are also noticeable seasonal variations in the use of human capital in the primary sector. However, these changes remain at the 1% level and do not hold substantial significance for the analysis.

The second component (HCK_2) has an even weaker effect on overall structural changes. It shows the interaction between changes in the share of human capital utilized and productivity in each individual industry. The dynamics of HCK_2 indicate that industries with low productivity slightly increased their share in the total utilization of human capital. Compared to the first quarter of 2017, in 2022 the largest changes at 0,5% occurred in the primary sector, but they are also insignificant. The third component (HCK_3) explains most of the variation because it measures each industry's contribution to productivity growth, weighted by its share of accumulated man-years of relevant education. The economy is dominated by low- and medium-tech manufacturing; this sector reacts most sharply to external shocks in the form of a pandemic and the second wave of sanctions restrictions. Amid the pandemic, a decline of approximately 4% was observed, followed by a brief period of recovery. However, by the third quarter of

2022, growth had plateaued at 3% for manufacturing and 2% for the financial sector, when compared to early 2017.

The analysis leads to the conclusion that sustainable growth was observed throughout the entire period only in the financial sector, which benefited from exchange rate differences. While the overall growth in the sector's value-added was 7% during the period, the increase in the average age of employees somewhat diminished this indicator. Notably, the financial sector experienced the most significant aging of its workforce, with the average age of employees rising by 5,4% since 2017. Conversely, high-tech sectors, such as ICT services, manufacturing, scientific research, and development, did not exhibit substantial dynamics. Overall, the observed structural changes align with the observations made by Fagerberg (2000) over a longer timeframe. The first and second indicators explain only a small portion of the change, while the majority of growth emanates from the third indicator, which encompasses the total growth weighted by each industry's share.

Conclusion

Reproduction of human capital in Russia has encountered several challenges over the past decade, including two waves of sanctions, the pandemic, and the demographic crisis. These circumstances have notably restricted access to foreign technologies, which are crucial for both the manufacturing and service sectors, and have slowed the inflow of young labor into the labor market. To study the dynamics of changes in the structural redistribution of human capital between industries, a non-conventional modification of the shift-share decomposition model (Fagerberg, 2000) is proposed. The change in value added as an indicator of economic growth in itself only gives a general idea of the quality of the labor force. Labor productivity, while informative, also has limitations in assessing the competitiveness of knowledge within the national economy relative to the actual labor supply. This study focuses on productivity in terms of the stock of accumulated education and work experience relevant to the labor market. The author believes that comparing the indicator with the dynamics of changes in GDP makes it possible to determine how much each added man-year of education and production experience brings an additional unit of added value to the economy. The higher the gap between human capital productivity and overall GDP growth, the less effective is the investment in each subsequent year of education and work experience.

The reviewed period is characterized primarily by changes in the age composition of the workforce. The proposed indicator of relevant educational capital and expected experience exhibits a strong correlation with the age of employed workers. This correlation, combined with the observed retention of educational attainment, suggests a negative impact, primarily due to demographic issues. Given that older age cohorts possess lower-quality human capital but are increasingly participating in the labor market, it becomes evident that the demographic challenges, will have enduring and adverse effects on the national labor market. The observed dynamics, first of all, emphasize the threat of technological regression, that is, the lack of innovations and basic technologies that are significant for the entire economy, supporting infrastructure and institutional development. Over the period under review, companies in high-tech sectors were unable to create a qualitatively new and efficient workforce that would generate a high level of added value. Such a transformation is likely to take years, exacerbating technological gaps and reducing the international competitiveness of national economy.

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