Adult learning and labour market outcomes: the moderating role of varieties of Russian state-led regional economies between 2013 and 2023

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Adult learning and upskilling (AL) strategies and outcomes are deeply influenced by the institutional context, which varies across regions in terms of coordination, regulation, specialization, informality, and knowledge intensity. This study examines how regional varieties of market economies moderate the impact of AL on labour market outcomes, focusing on non-formal education and online self-learning. Unlike previous research, this study uses social capital and perceived respect as additional outcome measures. To capture regional variations in market economies, we apply factor and cluster analyses based on the regional varieties of capitalism theory. Panel regressions with fixed effects and hybrid models are used to examine within- and between-cluster effects of AL on individual labour market outcomes. The research focuses on the case of 82 Russian regions from 2013 to 2023, utilizing Federal State Statistics Service (Rosstat) data and a panel sample from the Russian Longitudinal Monitoring Survey. The findings identify four key factors shaping regional varieties of market economies: knowledge intensity, social inequality, labour market informality, and resource dependence. Five types of regional variations of Russia's state-led market economy are identified. The study reveals age- and gender-related heterogeneity in the impact of AL on within-individual labour market outcomes, and robust, positive outcomes across individuals, resulting in wage premiums up to 30%. Differences in wages, job satisfaction, trust, and perceived respect across regions can largely be explained by underlying institutional characteristics. Knowledge-intensive regions tend to have more liberal, competitive labour markets, whereas resource-dependent regions exhibit more coordinated environments. Both types of regions positively impact wages across individuals. Moderation analysis indicates that coordinated environments in resource-dependent regions enhance the returns to non-formal AL, yielding better wage outcomes when local employers provide education. In contrast, knowledge-intensive regions exhibit a significant negative interaction between self-learning and job satisfaction, suggesting that the benefits of AL may be context-dependent.

Keywords:
adult learning,
upskilling,
human capital,
regional varieties of capitalism,
knowledge intensity,
natural resource dependency

Introduction

Adult learning and upskilling (AL) constitute a central component of national labour markets, representing a critical investment in human capital for middle-aged and older individuals. As a key component of lifelong learning strategies, AL takes various forms: formal education that leads to qualifications and degrees, structured non-formal training designed to prevent skill obsolescence, and self-directed learning driven by individual initiative. Deeply embedded in the socio-economic context, AL not only shapes individual labour market trajectories but also contributes to the reproduction of social capital, while enhancing individuals' autonomy and control over their lives (Holford et al. 2023). Thus, AL exerts a positive influence on various labour market outcomes, including employment opportunities, job performance, earnings, job satisfaction, individual autonomy, and innovative capacities (Heller-Sahlgren 2023).

From an institutional perspective, AL is influenced by the structures, policies, and cultural norms established by labour markets, educational institutions, governments, and organizations. Institutions play a pivotal role in shaping the accessibility, quality, and relevance of learning programs by establishing regulatory frameworks, designing strategic policies, influencing curriculum development, and ensuring the timely updating of skills (Ioannidou–Desjardins 2020, Rees 2013). At the same time, the institutional context of AL is connected with the prevailing market economy regime, which varies across regions due to complex historical and socio-economic contexts and institutional configurations (Whalen 2022: p. 23). The market economy remains the primary mechanism for allocating scarce resources among competing priorities, leveraging private property, entrepreneurship, and technological innovation (Acemoglu et al. 2017). The varieties of capitalism (VoC) framework (Hall–Soskice 2001) explores differentiation in market structures, integrating insights from institutional perspectives and political economy. The VoC explains regional institutional differences – including those in labour markets, education systems, and industrial relations – by examining the degree of regulation, coordination, specialization, and formalization within economic systems (Lane–Myant 2007, Pinto et al. 2019). Over the past two decades, the VoC has provided valuable insights into two key areas. First, it has enhanced the understanding of regional differentiation in market regimes within countries, illustrating how local institutions influence economic behavior. Second, it has informed investment policies in human capital – particularly in AL and skills development – by elucidating how institutional settings vary across countries and regions, and how these differences impact labour market outcomes. From a regional VoC perspective, human capital is developed within diverse institutional contexts, including coordinated, dependent, and liberal market economies, each characterized by distinct mechanisms for skill formation and workforce integration.

However, most studies on regional varieties of market economies have focused primarily on broad differences in regulatory frameworks, often overlooking how local actors interpret and implement these rules in practice, a factor that significantly influences the outcomes of otherwise uniform national economic and labour market policies across diverse "sub-models" (Zhang–Peck 2016). In addition, previous studies have provided qualitative descriptions of regional economic models based on explanatory design; however, they lack empirical measures for systematic comparison. Finally, the effects of different regional market regimes on labour market outcomes of AL remain unclear, since the institutional environment serves as a moderating factor in the reproduction of human capital. Our study addresses these gaps by quantitatively examining regional differences in resource allocation logic, focusing on the specialization between innovation-driven and natural resource-driven models, the balance between informality and regulation, and variations in social inequality and social subsidies.

It is also evident that, in recent years, the institutional environment for AL has been transformed by technological and social changes (Coelli–Tabasso 2019, Heller-Sahlgren 2023). Institutional adjustments to demographic decline suggest that labour constraints will only increase over time, thereby reinforcing the need for policy reforms in regional human capital allocation, workforce training, and automation. In this study, we examine the case of regional variations within the Russian state-led market economy from 2013 to 2023, a period marked by two stages of escalation in geopolitical and economic fragmentation and subsequent sanctions pressure (Gimpelson 2022). Despite economic shocks, the Russian labour market maintained its characteristic adjustment mechanisms (Kapeliushnikov 2023a, 2023b). The recent sanctions crisis of 2022 triggered a series of regional transformation processes, leading to large-scale labour reallocation toward government-driven sectors, including increased employment in defense, logistics, and other strategic industries. The education system also experienced a shift from liberalization to a reversal toward sovereignty and isolation, in line with increasing geoeconomic fragmentation.

This study examines how the institutional environment moderates the impact of AL on labour market outcomes, using a quantitative assessment of regional market economy varieties. By building on and complementing previous work on AL within institutional contexts, this study develops a novel approach to analyse the effectiveness of investments in AL, accounting for regional differences in market economy structures. Our methodology employs regional statistics to differentiate market regimes and utilizes longitudinal panel data to analyse changes in wages, job satisfaction, social capital, and perceived respect associated with non-formal or self-directed learning strategies.

Theoretical background

Adult learning theoretical perspectives and labour market outcomes

The neoclassical theory of human capital, which emphasizes investment in knowledge, skills, and health as a means of enhancing individual productivity, has become one of the most influential theories explaining the role of education in ensuring individual and regional competitive advantages (Becker 1993, Schultz 1961). Becker (1993) views continuous education, including AL, as a mechanism for adapting to technological change and labour market shifts, based primarily on individual choices and firm-level decisions. In the context of technological change, investments in education play a significant role in shaping both monetary and non-monetary labour market outcomes for individuals, prompting labour markets to enhance the knowledge and skills of the existing workforce (Psacharopoulos–Patrinos 2004). First, fundamental works on adult education and upskilling have examined the expansion and liberalization of learning strategies that cover a wide range of areas. These include global trends in social and technological transformation, as well as the balance between formal education and self-directed learning in the context of an increasingly complex environment for the reproduction of human capital (Jarvis 2004).

The current stage of AL-related research focuses on multidisciplinary, evidence-based policy approaches aimed at overcoming structural vulnerabilities and inequalities, addressing shortcomings within formal education systems, and facilitating smoother transitions from school to work and from work to retirement, with attention to regional contexts (Holford et al. 2023). The concept of AL has undergone significant transformation in recent years, driven by several factors. First, educational strategies have evolved as the role of self-education has expanded. The digital environment now offers a range of flexible avenues for knowledge acquisition, reducing dependence on institutional coordination and empowering individual learning efforts (Begen–Atasoy 2024, Sengupta et al. 2023). Second, a range of trends and external shocks have increased the cost of investing in human capital. Growing uncertainty is evident as education strategies are influenced by demographic, technological, geopolitical, and climate constraints (Holford–Michie 2024, Thwe–Kálmán 2024). Third, the dominant neoliberal perspective in education within developed countries has hindered the development of an integrated theoretical framework that brings together economic, sociological, and normative ideas. The focus of education has shifted from preparing adults for technological changes and social purpose education to an emphasis on social justice, diversity, and equality, thereby favoring individualism over collectivism (Gouthro 2022).

According to human capital theory, training enables different population cohorts to enhance their human capital, thereby improving individual productivity and supporting positive engagement within the labour market (Becker 1993, Heller-Sahlgren 2023). Alternatively, certificates, including those obtained through modern forms of non-formal digital learning, can be seen as signals to the labour market (Sengupta et al. 2023, Spence 1973). However, empirical research reveals that AL yields mixed effects, ranging from positive to neutral and, in some cases, negative outcomes. Moreover, many recent studies have focused on employment, wages, and job satisfaction. Heller-Sahlgren's (2023) study analyses the relationship between AL and employment outcomes, revealing that individuals who engaged in AL were 4 percentage points more likely to be employed compared to those who did not. The effect is more pronounced for full-time employment and is driven by non-formal, job-related training, such as on-the-job training, courses, and workshops. In contrast, Coelli–Tabasso (2019) examine lifelong learning in Australia and find that AL leads to modest or no increases in employment probability; wage gains are significant only for males, and no improvement in occupational prestige is observed following participation in formal education. AL is often driven by motivations beyond higher wages, including aspirations for career change, job transition, or personal development, self-improvement, rather than strictly economic reasons. However, there is evidence that short-term career and technical education is associated with an average-earnings increase of 14% among adult learners (Stevens et al. 2019). Begen–Atasoy (2024) demonstrate that technological literacy and the adoption of online learning positively influence employment outcomes: course enrollment, self-learning, and communication-based learning significantly enhance the likelihood of employment, particularly for women and older individuals, by offering flexible opportunities.

In addition to direct individual benefits in the form of employment and increased earnings, AL has broader social implications. Lifelong learning and vocational training, as key investment areas, are viewed not merely as tools for enhancing economic productivity but also as means for individuals to achieve personal well-being, agency, and societal participation (Holford et al. 2023). On the one hand, the increasing intensity of investment in human capital may also contribute to increased inequality and a decline in social mobility (Lopes–Carreira 2020, Saar–Räis 2017). Moreover, the continuing ideological role of education also generates normative uncertainty, thereby increasing the risks of insecurity in career decisions and diminishing professional autonomy. On the other hand, the liberalization of AL fosters individualization, context-specific critical thinking skills, and personal autonomy, leading to positive outcomes for individuals facing prolonged unemployment (Almeida–Morais 2024). AL serves as a key mechanism for reproduction and development of social capital, as reflected through social connections, trust, and shared values (Field 2005). Recent research has placed considerable emphasis on the impact of AL on democratic values, civic engagement, and empowerment (Haren Conely–Cordie 2023). AL empowers individuals to transform societal norms and create opportunities for greater control over their lives and career development, thereby enhancing their perceived respect. Tandon–Srinivasan (2024) show that adult education fosters empowerment, particularly showing how everyday experiences enable individuals to develop agency, challenge inequalities, and drive social change.

Institutional perspective: regional varieties of market economies and their impact on AL and its outcomes

Complementing and extending neoclassical economics – which offers a simplified yet clear, efficiency-driven framework for labour markets, human capital, and AL – the institutional perspective proposes a more context-sensitive analysis (Herbrechter–Schemmann 2022, Schemmann et al. 2020). Over the past decades, it has become evident that institutions vary significantly across national market economies, leading to the identification of ideal types that explain how differing levels of coordination influence strategies for regional resource allocation. The VoC theory developed by Hall–Soskice (2001) has gained considerable attention, particularly in research examining education and the differences in learning strategies across different economic systems (Desjardins 2017, Ioannidou–Desjardins 2020, Rees 2013). The VoC approach to explaining how the institutional environment influences training strategies and their outcomes emphasizes the interaction between individual and structural factors. In a market economy, the demand for and supply of AL are driven by two key elements: individual human capital characteristics and broader institutional factors, such as industry-specific occupational requirements (Saar–Räis 2017). While individual skills often receive greater attention, institutional frameworks play an equally critical role in determining both the likelihood of participation in training and the effectiveness of such training.

By linking the institutional perspective on AL with the VoC framework, it becomes evident that the structure of market economies significantly influences learning strategies and their outcomes. *Liberal market economies*, such as the UK and USA, prioritize flexibility, promoting the development of broad, transferable skills that align with the demands of dynamic labour markets (Desjardins 2017). In contrast, *coordinated market economies*, such as Germany and Nordic countries, tend to emphasize industry-specific skills through structured vocational training and close partnerships between firms and educational institutions, where long-term skill reproduction is linked to industrial strategies. However, while coordinated economies tend to have more stable human capital strategies, they depend on spillovers originating from liberal capitalism (Acemoglu et al. 2017). Saar–Räis (2017) provide empirical evidence on the general relationship between AL and labour market skill demand across different economic regimes. Workers in high-skill demand occupations (especially in coordinated economies such as Denmark and Germany) are significantly more likely to receive training. In contrast, industries with low-skill demand in the Czech Republic and Estonia offer fewer training opportunities, regardless of worker education.

Nölke–Vliegenthart (2009) further extend the VoC framework by introducing the concept of *dependent market economies* to explain the economic structures of East Central European countries, which rely heavily on foreign investment from multinational corporations. Dependent economies support state-driven vocational training from socialist economies, while investing minimally in workplace-based training that addresses the needs of foreign investors. Such countries as Russia and China are referred to as *state-led market economies* characterized by strong state dominance, weak institutional structures with hybrid features, and an unpredictable business environment in which formal economic rules coexist with strong informal governance structures (Lane–Myant 2007). State-led economies favor national "champion" industries to gain economic power and employ direct state intervention to support them. Vocational and AL systems are strongly influenced by state policies that prioritize skills development for strategic industries, and tend to lack flexible, modular learning pathways, including limited opportunities for reskilling outside of state-led initiatives. In the modern period, geoeconomic competition and the threat of climate catastrophe further give market economies increasingly polymorphic features, thereby creating opportunities for state intervention in the economies and strengthening the state's role as a controller and owner of capital (Alami 2023).

Recent research has emphasized the differentiation of market economy from narrower and underexplored *regional perspectives*. Crouch et al. (2009) were among the first to argue that capitalism is not solely structured at the national level, but also exhibits regional and sectoral variations. Local institutions and production systems influence economic outcomes independently of national models. Regional governance mechanisms influence labour relations, education systems, and technological innovation; as a result, different regions within the same country may develop unique economic and learning models based on their industrial specialization (Ebner 2016). Schröder–Voelzkow (2016) further integrate sectoral, regional, and national levels of economic governance, arguing that regional economies develop distinct regulatory frameworks that can either facilitate or hinder the growth of specific industries and learning processes for building new industrial capabilities. The concept of "variegated capitalism" recognizes that multiple regional market economy models can coexist within a single country. In the case of China, several regional models of capitalism have emerged, each shaped by unique historical, political, and economic factors (Zhang–Peck 2016). Regional policies influence workforce development differently. While some regions prioritize low-cost, on-the-job training supported by private initiatives and family networks, others emphasize formal education and innovation. Pinto et al. (2019) examine the level of development and structural weaknesses of educational systems across European regions and highlight how institutional differences in market economies impact human capital allocation.

Despite attempts to quantitatively analyse differences among regional market economies, the concept of regional varieties of market economies remains primarily grounded in qualitative research and understanding the interactions in resource allocation based on a range of regional cases. However, an important consideration in developing AL in regions is the need for evidence-based economic policy (Pabst 2021), where the measurement of formalized indicators serves to reduce uncertainty and incorporate the everyday experiences of market economy actors. Using quantitative techniques, Ruhose et al. (2024) show that the reformation of institutional environment for AL increases accessibility and diversity while reducing the costs associated with AL. The authors controlled for regional factors such as GDP per capita, unemployment rates, population density, and the proportion of foreigners; however, these variables did not significantly influence the estimated effect of education reforms on AL participation. Marczuk (2024) points out that the institutional settings of labour market and educational systems also shape individual outcomes, thereby creating country-specific employment trajectories. Countries with strong, specific vocational training systems (e.g., Germany, Austria) tend to have smoother transitions into employment, reducing the need for AL later in life. In contrast, countries with generalist education systems (e.g., UK, Southern Europe) often experience turbulent transitions into employment and require greater engagement in AL to compensate for skill mismatches. Literature review indicates that regional differences in the context of AL have been studied in a number of recent studies. Authors typically use gross regional product (GRP) to differentiate regions, and employment status and wages as the primary outcomes. However, GRP most likely reflects only the interaction of regional environmental factors, while resource allocation regimes in local markets depend on a significant number of variables, including inequality, labour market dynamics, and technological development. Evidence from European regions indicates that technological change and greater firm engagement in research and development (R&D) increase the likelihood of employee engagement in workplace learning (Neycheva–Baltov 2024). Consequently, the regional context of AL is also defined by the knowledge economy and knowledge intensity.

The Russian context of labour markets and AL

The Russian economy has been undergoing a post-socialist transformation for several decades (Dabrowski 2023). The shift toward a centralized and highly state-coordinated national formal education system was supported by standardized and centralized investment programs (Prakhov 2023). The market transition stimulated the demand for AL in fields such as economics, finance, and law to support the emerging market-type institutions (Alexeev 2023). AL had to become an important strategy for the Russian economy, as it faced a sharp devaluation of human capital among older cohorts of the population (Chernina–Gimpelson 2023). Initially, regulators' interest in developing and implementing education liberalization strategies was supported by the ideas of innovation and a knowledge-intensive economy. However, these initiatives struggled to take root amid the bureaucratized hierarchy and corruption risks prevalent in the early 2010s. Following the weakening of expectations from innovative development, the resource dependence model persisted as the leading framework supporting the state-led market model. Consequently, the Russian economy underwent a gradual and noticeable transformation, shifting from neoliberal models that promised integration, to a tendency toward oligarchic capitalism, and eventually to the establishment of state capitalism (Cerami 2009, Lane–Myant 2007: p. 153). In addition, after the 2010s, the demographic potential for the reproduction of human capital declined, and following 2014, incomes and the ability of households to invest in education and health dropped significantly (Avdeeva 2024). Hinz–Monastyrenko (2022) demonstrate that the population bears the burden of political decisions and experiences restrictions in access to technologies and specific goods. During the two waves of sanctions crisis post-2014, real wages stagnated despite significant growth in job vacancies and hiring activities, indicating a growing labour shortage and a reduction in labour costs and investments in human capital (Kapeliushnikov 2023b).

The *institutional environment of education* is national-specific, including formal strategies, initiatives, and funding projects. In the past decade, lifelong education and AL have received widespread support, including federal grants (Korshunov et al. 2020), regional monitoring projects for lifelong education (Fedotov et al. 2020), and comprehensive projects on supplementary education, employment promotion, and demographic policies (Korshunov et al. 2023). Weak partnership ties between businesses and educational institutions, the lack of forecast-based strategic approaches, and the isolation of labour market and educational services continue to represent vulnerabilities within the national AL model. Organizations supporting AL are considered part of the centralized education system, and their level of development is largely determined by the availability of regional resources. A large-scale empirical study on AL institutional determinants by Korshunov et al. (2023) shows that, in the Russian context, regions with higher levels of GRP demonstrate greater employee engagement in AL. Differentiation in participation rates is also evident at the sectoral level, depending on knowledge intensity: technology-intensive industries tend to attract more skilled workers and seek to invest in human capital.

Regional *labour markets* and their coordination mechanisms also reflect national specificities and determine the outcomes of AL strategies. In Russia, regional differences play a major role in shaping labour market outcomes, including wages, with their impact far exceeding those of individual and industry-specific characteristics (Lukyanova 2011). Law enforcement and unionization have traditionally exerted minimal influence, with weak regional differentiation. Although these institutions may formally resemble those in coordinated economies, in practice they function in a decentralized manner and are heavily influenced by informal mechanisms. The economic dimension of regional variations in the institutional environment can be measured in terms of agglomeration levels, investment flows, tax revenues, dependence on subsidies, natural resource and industrial specialization, as well as the structure and dynamics of export revenues (Zubarevich 2022). Zemtsov–Voloshinskaya (2024) introduce indicators of complexity, industrial specialization, and the effects of sanctions as key factors in explaining regional institutional differences. Their findings highlight the role of economic diversification – particularly the development of non-resource, knowledge-intensive industries – in increasing regional complexity, which, in turn, enhances resilience and accelerates the recovery of local labour markets following external shocks.

Based on our literature review, we conclude that the effects of AL on labour market outcomes are strongly influenced by regional context, including inequality, the structure of industrial specialization, and the degree of informality. Consequently, we propose the following research questions:

1. How do regional state-led market economies differ in their resource allocation regimes, particularly in terms of knowledge intensity, informality, inequality, and specialization?

2. What impact do AL and regional market economy characteristics have on labour market outcomes, such as wages, job satisfaction, trust in colleagues, and perceived respect?

3. How does the effect of AL on both within- and between-individual labour market outcomes vary across different market economy regimes in regional contexts?

Methods and data

Factor and cluster analysis of regional varieties of market economies

The study is based on a multi-stage approach. Although the analysis focuses on regions within a single national economy, the literature review indicates that regional variations do emerge, so that while regulatory frameworks remain uniform, their local interpretations by economic agents are influenced by historical and geographical contexts.

First, a principal component factor analysis was employed to identify implicit variables that explain regional differences in market economy regimes. The exploratory analysis technique enabled the identification and interpretation of factors underlying regional differences in market economy regimes, specifically in terms of inequality, the impact of formal coordination on the labour market, and dependence on natural resources. The variables selected for the analysis are detailed in the Results and discussion section, and include indicators of innovation, entrepreneurial activity, the Gini coefficient, level of regional specialization based on the sectoral structure of the GRP, structure of household income, level of social subsidies, and government expenditure in the region.

Second, a *k*-means cluster analysis was used to establish stable configurations within regional economic regimes. To determine the optimal number of clusters, the NbClust package in R was used (Masoura–Malefaki 2023); the application of the package showed that the optimal number of clusters is 5. For each region, cluster affiliation varies depending on the year; however, differences and transitions between clusters during the period may be insignificant. Therefore, the median cluster for each region was selected for a generalized analysis of the entire period under consideration. Cluster and factor analyses were employed as exploratory tools, and the interpretation of the obtained results is discussed in the Results and discussion section.

The period from 2013 to 2023 was chosen as the period for analysis. This period is characterized by the consolidation of regulatory efforts and the strengthening of state presence in economic sectors to enforce state-led capitalism as the key model of production and resource allocation. It covers two episodes of deliberate reversals in integration policies, resulting in the sanctions crises of 2014 and 2022. In addition, gradual changes occur during the period, demonstrating stable algorithms for the accommodation of the national labour market to economic downturns (Kapeliushnikov 2023a). Despite the trend of integrational reversal, during this period the transition to the international Bologna system was fully implemented, and one of the most influential programs to support the global integration of universities, "5–100", was introduced (Prakhov 2023).

Regression analysis

To assess the direct impact of AL on labour market outcomes and regional moderation effects, we performed regression analysis. The ordinary least squares (OLS) pooled regressions with year fixed effects tend to produce "naïve" estimates and simply show the extent to which AL affects labour market outcomes between individuals (Johnston–Lee 2013). Such estimates are likely to be biased because they do not account for the panel nature of the data, where an individual is sampled multiple times over several years. In the first stage of the regression analysis, we used fixed effects panel regression to determine the effects of variables on various labour market outcomes, allowing us to identify differences within individuals. The study thus addresses potential endogeneity issues by using fixed effects panel regression to account for idiosyncratic differences due to innate ability. The model was as follows:

$$L_{rit}=\beta_{r0}+\beta_{rn}S_{rit}+\beta_{rl}D_{rit}+\sum_{f=-5}^{5}\beta_{rf}AL_{rit}+\beta_{rm}REG_{rit}+\mu_{rf}AL_{rit}\times REG_{rit}+\delta_{rit}+t+\varepsilon_{rit} \quad (1)$$

The dependent variable is L – r labour market outcomes of individual i in the time period t (for the year dummy variables, 2013 was set as the reference year), such as log of wage, job satisfaction, social capital in the form of trust in colleagues, and perceived respect. The independent variables include a vector of time-varying labour supply variables S_{rit} reflecting accumulated human capital and socio-demographic characteristics, as well as a vector of labour demand variables D_{rit} reflecting the industry of work and profession. The variables of interest include f dummies of AL in vocational courses during the last 12 months (non-formal learning) and online learning during the last 12 months (self-learning). The indicator $AL_f = 1$ in the years during which AL occurred. It is calculated so that the period $f = –5$ corresponds to 5 years before training, and $f = 5$ to 5 years after training; therefore, when $f = 0$, $AL_0 = 1$. The coefficient β_{rf} shows the changes in individual labour market outcomes for persons who received training within the specified period. For identification, we exclude the period $f = –1$, the year before training. This approach allows us to consider the trend in individual earnings that was observed before and after training (Stevens et al. 2019). The vector of regional variables *REG* included the factor scores from previous factor analysis, reflecting variations in market economy regimes. Individual fixed variables δ_{rit} are included in the model based on its definition, and the equation also contains error terms ε_{rit}.

To assess the plausibility of the parallel trends-assumption (Wooldridge 2021), we conducted a formal Wald test on the joint significance of the pre-treatment coefficients for AL (i.e., years –5 to –2 relative to the treatment event) and provided a visual inspection of the event-time regression coefficient plots reported in the Appendix. The corresponding pre-treatment Wald tests for coefficients are reported in the regression tables presenting the fixed effects estimates.

The focus is on the coefficient μ_{rf}, which shows the effect of the interaction between AL and variables reflecting the regional variations in market economies within a single national regulatory context. Moderation occurs when the strength or direction of the relationship between a dependent variable (L) and an independent variable (AL) changes depending on the level of a moderator variable (REG). The coefficient thus enables us to assess the influence of the conditions for implementing AL strategies on labour market outcomes. The vector of regional variables *REG* at the stage of fixed effects models includes previously calculated factor scores only. To explore the role of regional context in moderating AL labour market outcomes, we also estimated extended fixed effects models with $REG \times t$ and $AL \times REG \times t$ interactions. The specifications allow us to test whether both baseline trends and the effects of AL vary across regional institutional types over time. Due to the large number of coefficients, we summarize only key patterns in the Results and discussion section.

In the fixed effects models, the coefficients capture how within-individual changes over time (e.g., starting a new AL activity or changes in a region) correlate with changes in that individual's labour market outcomes. Time-invariant individual characteristics (e.g., innate ability, baseline education) are controlled for by the fixed effects estimator, which captures within-individual variation over time. Our focus, however, is on how regional institutional characteristics, represented by factor scores and clusters, moderate the effects of AL. Although these regional variables change little over time, they can still be validly used in interaction terms, as adult learning varies at the individual level. This is particularly relevant given the Russian Longitudinal Monitoring Survey (RLMS) structure, where individuals rarely change regions. Therefore, in the second stage of our analysis, we apply a *hybrid model* using generalized linear mixed models (GLMM) to estimate both within-individual effects and cross-regional heterogeneity (Schunck–Perales 2017). This approach allows for the inclusion of dummy variables representing cluster membership in the equation to analyse both direct and moderation effects. Since only 37 regions are represented in the RLMS, we analysed the effects in *knowledge-intensive regions* with a relatively high level of innovation and entrepreneurial activity (cluster 3) and *resource-dependent regions* (cluster 4), with the reference group consisting of neutral regions (clusters 1, 2) and regions with high informality (cluster 5).

The advantage of the hybrid approach lies in its combination of random and fixed effects models, which allows tracking differences in labour market outcomes at two levels using the link function $g(\cdot)$. The panel data are hence clustered to obtain the following structure: the level-two units are individuals and the level-one units are person-year observations. Ignoring this structure can lead to biased estimates and incorrect inferences because observations within the same cluster tend to be more similar than observations from different clusters. The hybrid model extends traditional GLMMs by decomposing level-one variables into two components, so the independent variables in vector X_{it} may vary both within (β_W) and between (β_B) clusters. Moreover, the model includes level-two covariates c and cluster-specific random effect u:

$$g(L_{il})=\beta_W(X_{it} - \overline{X}_i) + \beta_B X_i+\gamma c_i+u_i \qquad (2)$$

A common approach to isolate within-cluster effects is group-mean centering. To capture the between-cluster effect, we include the cluster-level mean X_i as a predictor in the model. In our specifications, we include level-one variables that vary between and within clusters, such as supply and demand factors of labour and regional variables; however, the level-two gender variable varies only between clusters. Gender does not change within-individual over time and is estimated in the same way as in a standard random-effects model.

Heterogeneity

The literature review shows the importance of accounting for sample heterogeneity when examining the effects of AL on labour market outcomes. In this regard, we estimate the specifications of the models for men and women separately, considering their distinct roles in the national labour market, resulting in significant gender differences in participation rates and shorter education spells (Zoch 2023). Building on the results of previous studies in the Russian context, we also assume that women are more likely to participate in education and are more likely to be employed in the public sector, which offers social guarantees (Baskakova–Chubarova 2021). In addition, employers are more likely to offer training to men than to women; as a result, the latter increasingly prefer self-education. Previous studies in the field of AL have also identified heterogeneity across age groups of the population, distinguishing the effects for young adults and older cohorts aged 40 and above (Coelli–Tabasso 2019). Our study period from 2013 to 2023 also encompasses a significant economic shock during the pandemic, which had a notable impact on self-learning strategies, particularly in the context of online learning. In line with recommendations from earlier studies, we further estimate the effects before and after the pandemic (Begen–Atasoy 2024).

Data

To analyse regional variations in market economies, we employed Rosstat (2024a, 2024b, 2024c) data covering all 82 regions of Russia as of early 2013. Unlike previous studies on local labour markets (Oshchepkov 2020), we included all regions in the analysis, including the southern republics, in order to have a comprehensive picture of regional diversity in market economy regimes. Although local labour markets may form inter-territorial clusters, our analysis uses administrative divisions because state and social policies (e.g., social subsidies to reduce inequality) are determined by regional borders. We acknowledge, however, that cross-border differentiation in labour markets and human capital remains understudied. Though recent research shows that, after 2022, there has been an increase in the volatility and uncertainty of Russian economic statistics, particularly related to tax revenue, corporate profits, as well as a decline in the explanatory power of budget-related indicators (Simola 2024), we consider the impact of possible inconsistencies to be overall insignificant in the context of our research.

To analyse the impact of regional differences on AL and labour market outcomes, we used data from the RLMS (Higher School of Economics 2024). The RLMS database is the only longitudinal panel study in Russia that provides detailed data on individuals in terms of human capital, wages, and other social characteristics. The data included individuals aged 25 to 64 who participated in the RLMS panel from 2013 to 2023. The RLMS sample includes only 37 regions out of 82 that were used for factor and cluster analyses. A total sample of 59,809 observations was used for the period, combining panel data on 6,186 men and 7,171 women.

Results and discussion

Results of factor and cluster analyses

The identified factors are latent variables derived from observed variables that capture specific aspects of regional socio-economic policy. Drawing on the literature, we selected indicators expected to most significantly influence regional labour market differentiation and that were consistently available throughout the study period (see Table 1). The factor analysis employs a relatively conservative set of observable variables, yet it reliably reveals the underlying relationships driving regional variations in market economies. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy is 0.6, which is acceptable, and the model explained a total of 69% of the variance in the data. Bartlett's test of sphericity ($\chi^2 = 4835$, $p = 0.000$) confirmed strong correlations among the variables. We combine several statistical indicators recommended by previous studies that examined regional variations in market economies using factor analysis, particularly those focusing on the regulation of the business environment, labour markets, and social cohesion (Lane–Myant 2007: p. 44). Exploring regional context, we also account for the institutional specificity of the state-led economies. *Trade unions* tend to be weak and largely ineffective at wage bargaining. Rather than relying on collective bargaining, wage setting in these contexts is highly decentralized, with bonuses and informal variable payments playing a crucial role in the wage structure. Moreover, *minimum wages* exhibit minimal regional variation, are set at relatively low levels, and are often not enforced, allowing significant downward flexibility in wages. *Unemployment rates* are also of limited relevance, as the government prioritizes low unemployment and exerts pressure on firms to retain workers during crises through wage subsidies and other support measures, rather than by stimulating job creation. Instead, we use the ratio of unemployed persons per vacancy as a more accurate indicator of job availability in each region.

The first factor reflects a region's *knowledge intensity*, distinguishing areas that specialize in high-productivity industries from those reliant on natural resource-based sectors. This factor combines indicators of knowledge intensity with a high share of property income, and it is associated with local market liberalization in state-led models, increased entrepreneurial activity, and a decreased reliance on social subsidies.

Table 1

Results of factor analysis

Observed variables	Knowledge intensity	Social inequality	Labour market informality	Resource specialization	Variance extracted, %
Number R&D personnel per 1,000 population (Rosstat 2024a)	**0.926**	0.222	–0.069	–0.108	29.56
R&D total expenses in 2016 prices, share of GRP, % (Rosstat 2024a)	**0.835**	0.099	–0.024	–0.221	
Property income, % of total income (Rosstat 2024a)	**0.708**	0.044	–0.375	–0.046	
Gini index (Rosstat 2024b)	0.136	**0.881**	–0.076	0.112	18.57
Social subsidies, % of total households' income (Rosstat 2024a)	–0.227	**–0.826**	0.148	0.012	
Unemployed per one vacancy (Rosstat 2024a)	–0.025	0.031	**0.755**	–0.062	11.23
Government expenditure, % of GRP (Rosstat, 2024a)	–0.031	–0.359	**0.659**	0.318	
Informal labour share, % of employed (Rosstat 2024c)	–0.483	0.014	**0.600**	–0.368	
Small and entrepreneurial business employment, % (Rosstat 2024a)	0.239	0.207	**–0.573**	–0.084	
Share of unprofitable organizations (Rosstat 2024a)	–0.091	–0.137	–0.028	**0.716**	9.7
Share of natural resource production in GRP (Rosstat 2024a)	–0.248	0.499	–0.196	**0.627**	
Share of industrial sector in GRP, % (Rosstat 2024a)	0.114	–0.316	–0.318	**–0.700**	

The second factor integrates the Gini index with the share of social investment in income to capture levels of *social inequality*. In regions with substantial social subsidies, inequality remains minimal, whereas a higher share of private income is linked to significant inequality, as observed in the Russian market model. In low-inequality areas, state intervention often aims to mitigate social tensions, particularly when overall income levels are low.

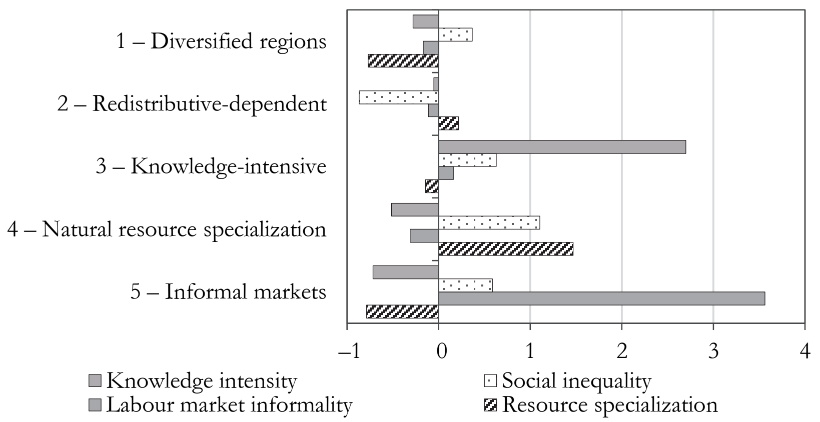
The third factor measures the *informality of labour markets*, as indicated by the proportion of workers operating outside formal regulation. Higher informality is associated with increased formal unemployment, a scarcity of job vacancies, and underdeveloped entrepreneurial activity that fails to generate employment. Additionally, a relatively large share of government spending allocated to administration and the maintenance of social infrastructure in these regions suggests low value addition, further increasing dependence on government subsidies.

Finally, the fourth factor reflects the degree of *specialization in resource industries* versus manufacturing. Regions with a strong specialization in resource sectors tend to enforce stricter industry regulations, which significantly reduce the size of the informal sector. However, resource specialization also introduces greater financial volatility and a higher incidence of unprofitable organizations, particularly during periods of resource market fluctuations.

Based on these four factors, we identified five clusters of regions, each exhibiting distinct configurations in terms of specialization, inequality, and informality. Descriptive statistics for each cluster, including GRP, unionization, and unemployment indicators, are presented in the Appendix Table A1. The cluster configurations are shown in Figure 1. A region's cluster affiliation may change over time because clustering was performed on a region-by-year basis; in subsequent analyses, we use the cluster membership corresponding to each specific year. Overall, movements between clusters are minimal, consistent with previous studies that document a strong path dependency in regional development (Kapeliushnikov 2023a, Oshchepkov 2020). The most notable transitions occur between the first and second clusters, which share several similar characteristics, whereas clusters representing resource- and knowledge-intensive regions remain relatively stable throughout the study period.

Figure 1

Cluster configurations



Note: mean values for each factor score within clusters are presented.

For further classification of regions into clusters, we primarily rely on quantitative analysis to assess the specificity of the institutional environment, supplementing our findings with qualitative evidence and insights from the literature. The first cluster includes "neutral" regions with relatively diversified economic structures, geographically located in the central part of Russia, Siberia, and the Far East. *Diversified regions* typically have industrial specialization in several sectors, combining low levels of investment in research and development, low unemployment, and a significant share of profitable organizations. This cluster includes the capitals of federal districts, implying enhanced coordination of labour markets and increased funding for human capital development programs, for example, within the framework of federal university development initiatives (Prakhov 2023). Figure 2 illustrates the geographical distribution of the regions in this cluster.

The second cluster includes regions that do not have a clear industrial specialization and are characterized by low-efficiency labour markets, such as Tuva and the Altai Republic (Oshchepkov 2020). *Redistributive-dependent regions* demonstrate low added value and a relatively low level of per capita GRP, with social subsidies accounting for over a quarter of household income on average, significantly above the national average. They represent a dependent-type market economy with low levels of informality.

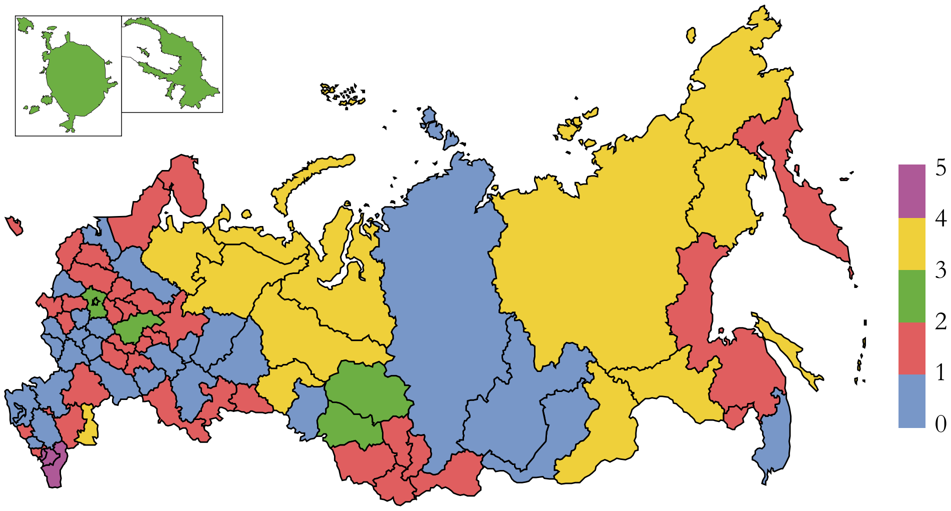
The third cluster groups regions with a high level of added value in the *knowledge-intensive* sector, including Moscow, St. Petersburg, and the Nizhny Novgorod and Novosibirsk regions. These regions are distinguished by a high level of entrepreneurial activity, demonstrating a liberal type of state-led market economy. A higher concentration of capital and per capita GRP is evident in property income, which constitutes an average of 6% of household income – double the national average. Knowledge-intensive regions record the lowest levels of informality and unemployment, suggesting that high coordination is effectively combined with substantial investments in high-value industries.

The fourth cluster includes regions specializing in *natural resources*, primarily in the oil and gas industry, and is characterized by the highest level of per capita GRP. Regulatory policies focus on supporting "champion" industries that form the core of the regional labour market and drive investments in human capital. Labour market coordination is high, dominated by a few large employers with highly formalized human capital management systems. Resource regions represent a coordinated type of regional market economy and traditionally demonstrate high income levels combined with high inequality.

Finally, the fifth cluster unites *informal labour markets*, which are subject to minimal coordination and are characterized by the lowest per capita GRP, minimal investments in industry and knowledge-intensive sectors, and elevated levels of unemployment. The cluster includes the southern republics, consistent with previous studies (Oshchepkov 2020). In some regions, a large informal sector enables firms and workers to bypass rigid formal labour laws, allowing employers greater flexibility in adjusting labour costs while permitting workers to avoid high taxation. However, this contributes to low-quality employment, which in turn undermines the effectiveness of strategies for the reproduction and deployment of human capital. These regions represent dependent-type market economy variations with high informality, providing greater flexibility to those participating in local informal networks.

Figure 2

Territorial distribution of clusters

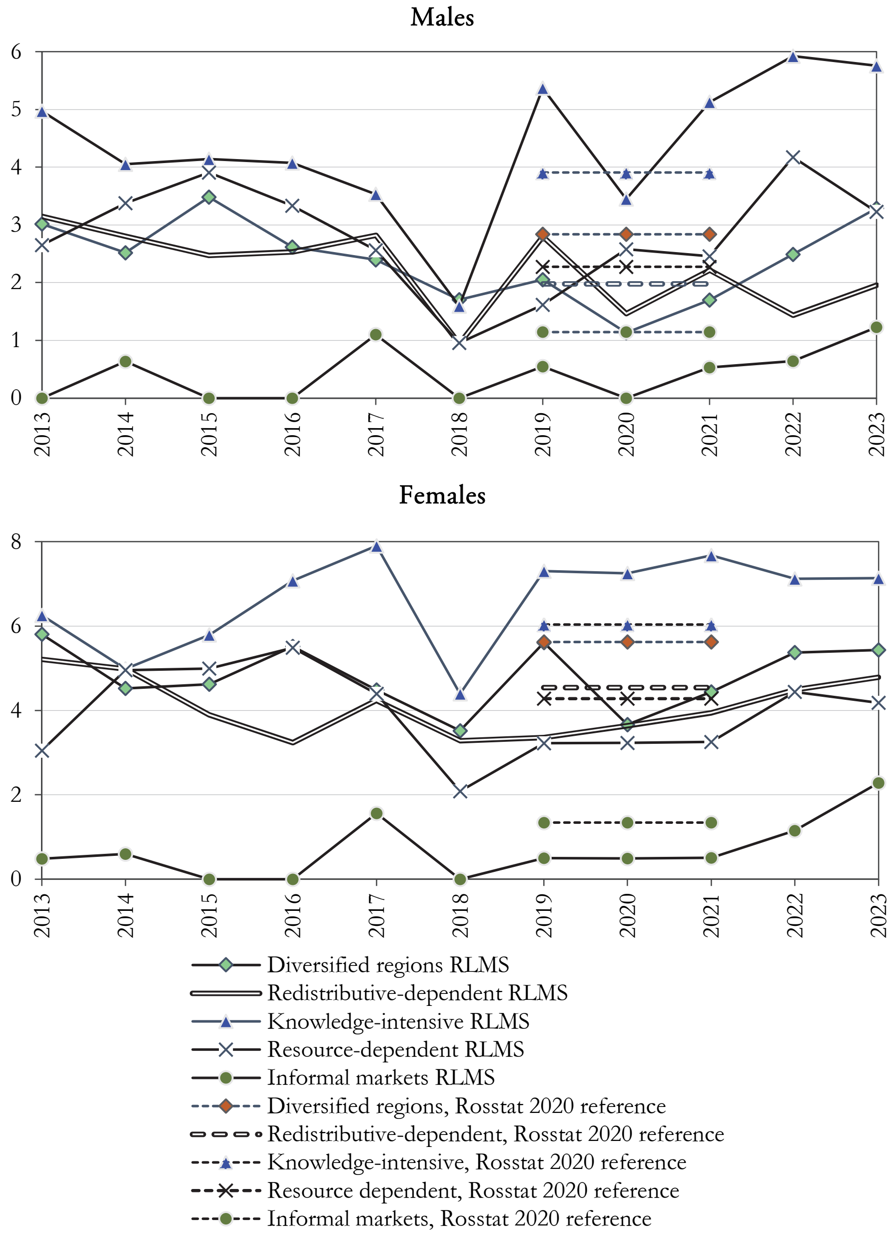


Note: median cluster number value for each region for the period from 2013 to 2023 is shown.

For each cluster, we assess the level of AL participation by men and women, comparing data from the RLMS panel with Rosstat's 2020 data (Rosstat 2024d) on non-formal education (see Figure 3). Rosstat monitors participation in continuing education at five-year intervals; however, comparable data for 2015 are unavailable due to methodological differences. We select non-formal learning as the primary indicator of participation. Typically, it occurs at the employer's initiative and is usually employer-funded, including short-term advanced training courses. The overall participation rate in non-formal AL during the 12 months preceding the survey ranges between 3% and 5% per year, aligning with Rosstat estimates. As expected, women participate more in vocational courses than men, with the highest participation rates observed in knowledge-intensive regions and the lowest in regions with informal labour markets. The pandemic did not significantly affect participation in non-formal education. Online self-study exhibits average participation rates of approximately 10% for men and 15% for women throughout the entire period.

Figure 3

Participation in AL by clusters, % of population (25–64 years old)



Results of regression analysis

Descriptive statistics for the RLMS sample used to estimate both within- and between-individual effects of AL are presented in the Appendix Table A2. The first type of panel regressions was based on model (1) with fixed effects, reflecting the within-individual effects of AL on labour market outcomes. In Tables 2–5 we report only the coefficients for variables directly relevant to the research questions regarding the moderating influence of the regional environment; therefore, the control variables for demand and supply from equations (1) and (2) were omitted. The coefficients reflect the impact of independent variables on labour market outcomes over each individual's life course, rather than differences between individuals. Based on the estimation of the $\sum_{f=-5}^{5} \beta_{rf} AL_{rit}$ coefficients, model (1) shows that AL directly enhances women's wages only during the first two years after training, while men who engage in self-training experience a steady decrease in job satisfaction (see in Appendix Figures A1 and A2).

The first dependent variable, reflecting the primary economic labour market outcome, was the logarithm of wage per hour (see Table 2). Direct effects of participation in non-formal education and self-learning are observed only for women. In the fixed effects model (1), factor scores (fs) are used as regional variables to reflect the degree of knowledge intensity, inequality, resource dependence, and informality in the regions. An increase in a region's level of knowledge intensity is associated with higher individual earnings. Higher levels of regional informality and social inequality also contribute to the growth of individual earnings over time. Moreover, an increase in informality in a region is more beneficial for women and does not have a significant impact on men's earnings. When regional informal markets are strong, women tend to prefer employment in the public sector, which offers them stable employment and earnings. Regional inequality is found to enhance within-individual earnings growth among men by shifting the earnings structure, specifically by reducing the share of state subsidies and increasing the proportion of labour income. Although a direct effect of AL is not observed for men, increased regional informality tends to significantly reduce their earnings in the post-education period, holding other factors constant. Using a Wald test, we failed to reject the null hypothesis of equal pre-AL years labour market outcomes (see Tables 2–3), providing support for the parallel trends assumption.

Table 2

Fixed effects panel regression estimates

Independent variables	Log of hourly wage				Job satisfaction			
	non-formal AL interaction		self-learning interaction		non-formal AL interaction		self-learning interaction	
	males	females	males	females	males	females	males	females
AL, courses	–0.018 (0.017)	0.071*** (0.018)	–0.001 (0.013)	0.066*** (0.014)	0.034 (0.035)	0.031 (0.024)	0.037 (0.027)	0.035 (0.019)
AL, self-learning	0.015 (0.010)	0.046*** (0.011)	0.016 (0.012)	0.044** (0.014)	–0.056** (0.020)	–0.009 (0.015)	–0.048 (0.026)	0.001 (0.018)
Knowledge intensity (fs)	0.053*** (0.010)	0.045** (0.012)	0.055*** (0.010)	0.048** (0.016)	0.094*** (0.026)	0.099*** (0.022)	0.096*** (0.026)	0.100*** (0.022)
Social inequality (fs)	0.077*** (0.011)	0.032* (0.013)	0.078*** (0.011)	–0.014 (0.017)	–0.013 (0.026)	0.033 (0.022)	–0.011 (0.026)	0.035 (0.023)
Labour market informality (fs)	0.003 (0.013)	0.057** (0.018)	0.007 (0.013)	0.066*** (0.018)	–0.001 (0.026)	0.005 (0.023)	0.006 (0.027)	–0.000 (0.023)
Resource specialization (fs)	–0.014 (0.014)	–0.018 (0.019)	–0.015 (0.014)	–0.018 (0.020)	–0.006 (0.029)	–0.027 (0.025)	–0.006 (0.029)	–0.031 (0.025)
Knowledge intensity (fs) × AL	0.006 (0.009)	–0.010 (0.009)	–0.010 (0.006)	–0.012 (0.007)	0.005 (0.018)	–0.002 (0.012)	–0.012 (0.013)	–0.002 (0.009)
Social inequality (fs) × AL	0.006 (0.017)	0.019 (0.018)	–0.005 (0.012)	0.013 (0.013)	0.027 (0.035)	0.012 (0.023)	–0.004 (0.025)	–0.003 (0.017)
Labour market informality (fs) × AL	–0.076* (0.030)	0.027 (0.031)	–0.072*** (0.020)	–0.047* (0.022)	0.071 (0.062)	–0.023 (0.040)	–0.038 (0.043)	0.019 (0.028)
Resource specialization (fs) × AL	0.018 (0.018)	0.003 (0.019)	0.034** (0.012)	0.004 (0.014)	0.018 (0.037)	0.002 (0.025)	0.024 (0.026)	0.026 (0.018)
Observations	26,503	33,306	26,503	33,306	26,503	33,306	26,503	33,306
Groups	6,186	7,171	6,186	7,171	6,186	7,171	6,186	7,171
Wald F-statistics and p-values for pre-AL years	1.41 (0.229)	0.49 (0.747)	1.26 (0.283)	0.59 (0.667)	0.45 (0.769)	0.91 (0.455)	0.43 (0.788)	0.65 (0.627)
R-squared (within)	0.272	0.192	0.273	0.192	0.030	0.023	0.030	0.023
F-statistics	222.8***	181.9***	223.5***	182.1***	17.9***	17.5***	17.9***	17.6***

Notes: marginal effects of AL on log wages and job satisfaction are shown. * p<0.05, ** p<0.01, *** p<0.001.

The next labour market outcome considered is job satisfaction (see Table 2). Satisfaction is measured on a five-point scale from complete satisfaction (5 points) to complete dissatisfaction (1 point). Although the models for job satisfaction have less explanatory power than those for earnings, salary remains the strongest predictor of satisfaction for both men and women. For men, self-training leads to a decrease in job satisfaction during the first two years after training. After the second year, the effect of AL becomes insignificant (see in Appendix Figure A1). Additionally, the coefficients indicate that an increase in regional knowledge intensity has a strong, positive, and significant effect on satisfaction for both genders, while other coefficients, particularly those reflecting interactions with regional variables, are not significant at the within-individual level.

Trust in colleagues is also considered as a dependent variable and was measured on a five-point scale, where 5 signifies complete trust and 1 signifies complete distrust. Trust is an important outcome because it reflects the level of social capital that fosters confidence and psychological safety at work, thereby enhancing subjective well-being (Field 2005). AL, as can be seen, does not have a direct within-individual effect (see Table 3). However, trust in colleagues increases with higher regional labour market informality, possibly because stronger clan cultures develop within local organizations under such circumstances. Furthermore, resource specialization in a region positively interacts with self-learning to enhance trust; this effect is significant for both men and women. In other words, the social capital benefits of self-learning are more evident in regions specialized in resource industries.

Table 3

Fixed effects panel regression estimates

Independent variables	Trust in colleagues				Perceived respect			
	non-formal AL interaction		self-learning interaction		non-formal AL interaction		self-learning interaction	
	males	females	males	females	males	females	males	females
AL, courses	0.029 (0.031)	0.039 (0.021)	0.048* (0.023)	0.067*** (0.020)	–0.087* (0.043)	–0.027 (0.037)	–0.088* (0.043)	–0.024 (0.037)
AL, self-learning	–0.005 (0.018)	–0.021 (0.013)	–0.034 (0.023)	0.002 (0.020)	–0.058 (0.043)	–0.006 (0.037)	–0.055 (0.043)	–0.002 (0.037)
Knowledge intensity (fs)	0.046* (0.023)	0.065** (0.020)	0.122*** (0.023)	0.049* (0.021)	0.040 (0.044)	–0.040 (0.038)	0.046 (0.044)	–0.045 (0.038)
Social inequality (fs)	–0.033 (0.023)	0.002 (0.020)	–0.009 (0.026)	–0.033 (0.022)	–0.052 (0.048)	–0.049 (0.041)	–0.057 (0.048)	–0.060 (0.042)
Labour market informality (fs)	0.122*** (0.023)	0.050* (0.020)	0.048* (0.023)	0.067*** (0.020)	–0.087* (0.043)	–0.027 (0.037)	–0.088* (0.043)	–0.024 (0.037)
Resource specialization (fs)	–0.002 (0.026)	–0.026 (0.022)	–0.034 (0.023)	0.002 (0.020)	–0.058 (0.043)	–0.006 (0.037)	–0.055 (0.043)	–0.002 (0.037)
Knowledge intensity (fs) × AL	0.009 (0.016)	0.000 (0.011)	–0.010 (0.012)	–0.012 (0.008)	–0.025 (0.030)	0.006 (0.020)	–0.002 (0.022)	–0.015 (0.015)
Social inequality (fs) × AL	–0.034 (0.031)	0.008 (0.020)	–0.013 (0.022)	0.007 (0.015)	0.054 (0.057)	0.014 (0.037)	–0.001 (0.042)	–0.001 (0.028)
Labour market informality (fs) × AL	0.070 (0.054)	0.042 (0.036)	0.026 (0.038)	0.012 (0.025)	0.089 (0.102)	0.143* (0.066)	–0.038 (0.071)	0.089 (0.046)
Resource specialization (fs) × AL	–0.016 (0.033)	0.049* (0.022)	0.055* (0.023)	0.055*** (0.016)	–0.009 (0.061)	0.008 (0.041)	0.064 (0.042)	0.065* (0.030)
Observations	26,503	33,306	26,503	33,306	26,503	33,306	26,503	33,306
Groups	6,186	7,171	6,186	7,171	6,186	7,171	6,186	7,171
Wald F-statistics and p-values for pre-AL years	0.25 (0.910)	1.26 (0.285)	0.49 (0.745)	1.96 (0.098)	1.78 (0.130)	1.86 (0.114)	0.72 (0.576)	1.24 (0.290)
R-squared (within)	0.013	0.008	0.013	0.008	0.013	0.012	0.013	0.010
F-statistics	7.34***	6.29***	7.45***	6.44***	7.79***	7.74***	7.80***	7.78***

Notes: marginal effects of AL on trust in colleagues and perceived respect are shown. * p<0.05, ** p<0.01, *** p<0.001.

In the RLMS, the perceived respect indicator is measured using the question: "Imagine a ladder with 9 steps, where the bottom step represents people who are not respected at all, and the top step represents those who are very respected. Which of the nine steps are you on today?" Both non-formal education and self-education contribute positively to perceived respect among women. Specifically, increases in regional knowledge intensity and higher social inequality are associated with improved self-assessments of perceived respect among women, whereas for men, this indicator is influenced primarily by the level of regional informality. The moderation effects are more pronounced for women: higher regional informality amplifies the positive return of self-learning in terms of perceived respect. We further analysed the estimations of the extended fixed effects models with $REG \times t$ and $AL \times REG \times t$ interactions. While most interaction terms are not statistically significant, we identified consistent negative trends in wages (2022–2023) and job satisfaction (2017–2023) in knowledge-intensive regions, suggesting declining labour market dynamics in these contexts regardless of AL. No significant regional differentiation is observed in the temporal pattern of AL effects, indicating limited evidence for dynamic institutional moderation.

In the second stage of regression analysis, we examined regional effects using hybrid models that capture both within- and between-individual variation. The sample for these hybrid models includes the entire population aged 25–64 years, and the coefficients for the gender dummy were estimated using the random effects method. Hybrid model (2) allows for the inclusion of cluster dummies in the equation. In fixed effects model (1), this is only possible when a region moves between clusters. As noted earlier, such transitions are rare, but they provide variations in the influence of regional context, which is why the coefficients are typically significant only for between-individual effects. In general, fixed effects for the entire population are similar to the estimates in model (1), which was estimated separately by gender. For instance, an increase in regional informality is associated with a relative decrease in wages following self-learning. Therefore, in the subsequent analysis, we focus on between-individual effects – comparing individuals to one another – and contrast these with within-individual effects.

First, we analyse the direct impact of AL on labour market outcomes at the between-individual level (see Tables 4 and 5). Overall, all forms of AL are associated with higher individual earnings. The positive effect is evident for women throughout their life course and becomes even more pronounced when comparing individuals regardless of gender. In contrast, the effects on job satisfaction and trust in colleagues are considerably less significant. In fact, individuals who participate in non-formal learning tend to report lower levels of trust in colleagues, and this effect is smoothed out in regions with high informality. However, individuals who have undergone training report significantly higher levels of perceived respect from others, whereas self-training appears to be associated with reduced perceived respect.

Second, we examine the influence of regional variables on labour market outcomes. Both knowledge intensity and resource dependence show strong, positive effects on earnings. Specifically, individuals in knowledge-intensive regions enjoy a substantial salary premium – approximately 35% – compared to a premium of 22% in resource-specialized regions. Despite these higher earnings, labour markets in knowledge-intensive regions are more competitive, and workers in these regions tend to experience lower levels of perceived respect. Conversely, resource-rich regions are associated with a notable increase in perceived respect. Regions with increased social inequality tend to exhibit higher comparative earnings and levels of perceived respect, while also demonstrating lower levels of trust and satisfaction. In regions with high informality, individuals face earnings losses that are partially offset by gains in satisfaction and trust, with a particularly strong positive effect on perceived respect.

Table 4

Hybrid model estimations for log of hourly wage and job satisfaction

Variables	Log of hourly wage				Job satisfaction			
	factor scores interaction		regional clusters interaction		factor scores interaction		regional clusters interaction	
	non-formal	self-learning	non-formal	self-learning	non-formal	self-learning	non-formal	self-learning
AL, non-formal (within)	0.050*** (0.013)	0.049*** (0.010)	0.054*** (0.013)	0.052*** (0.010)	0.037 (0.019)	0.039* (0.015)	0.029 (0.019)	0.041** (0.015)
AL, self-learning (within)	0.036*** (0.008)	0.037*** (0.009)	0.034*** (0.008)	0.040*** (0.009)	–0.019 (0.011)	–0.009 (0.014)	–0.022 (0.011)	–0.024 (0.014)
Knowledge intensity, (fs) (within)	0.056*** (0.009)	0.057*** (0.009)			0.124*** (0.014)	0.124*** (0.014)		
Social inequality, (fs) (within)	0.052*** (0.009)	0.052*** (0.009)			0.021 (0.013)	0.023 (0.013)		
Labour market informality, (fs) (within)	0.053*** (0.010)	0.059*** (0.010)			0.009 (0.016)	0.008 (0.016)		
Resource specialization, (fs) (within)	–0.017 (0.011)	–0.018 (0.011)			–0.032* (0.016)	–0.034* (0.016)		
Knowledge-intensive regions, dummy (within)			0.032 (0.020)	0.036 (0.020)			0.039 (0.030)	0.043 (0.030)
Resource specialized regions, dummy (within)			–0.023 (0.017)	–0.029 (0.017)			0.066** (0.025)	0.063* (0.025)
Knowledge intensity × AL, (within)	–0.005 (0.006)	–0.008 (0.005)			0.001 (0.010)	–0.003 (0.007)		
Social inequality × AL (within)	0.006 (0.012)	–0.002 (0.009)			0.014 (0.019)	–0.003 (0.014)		
Labour market informality × AL (within)	–0.007 (0.022)	–0.047** (0.015)			0.020 (0.033)	0.017 (0.023)		

(Table continues on the next page.)

(Continued.)

Variables	Log of hourly wage				Job satisfaction			
	factor scores interaction		regional clusters interaction		factor scores interaction		regional clusters interaction	
	non-formal	self-learning	non-formal	self-learning	non-formal	self-learning	non-formal	self-learning
Resource specialization × AL (within)	0.011 (0.013)	0.013 (0.010)			0.004 (0.020)	0.022 (0.014)		
Knowledge-intensive regions × AL (within)			–0.014 (0.020)	–0.039* (0.016)			0.034 (0.030)	–0.003 (0.024)
Resource specialized regions × AL (within)			–0.001 (0.032)	0.043 (0.024)			0.008 (0.049)	0.026 (0.037)
AL, non-formal (between)	0.305*** (0.037)	0.238*** (0.031)	0.220*** (0.041)	0.246*** (0.031)	0.043 (0.046)	0.026 (0.038)	0.053 (0.049)	0.029 (0.038)
AL, self-learning (between)	0.146*** (0.020)	0.193*** (0.024)	0.151*** (0.021)	0.117*** (0.025)	0.031 (0.025)	0.049 (0.030)	0.030 (0.025)	0.079** (0.030)
Knowledge intensity, (fs) (between)	0.082*** (0.003)	0.082*** (0.003)			–0.004 (0.004)	–0.001 (0.004)		
Social inequality, (fs) (between)	0.060*** (0.006)	0.062*** (0.007)			–0.021** (0.008)	–0.020* (0.008)		
Labour market informality, (fs) (between)	–0.067*** (0.010)	–0.077*** (0.011)			0.038** (0.012)	0.045*** (0.013)		
Resource specialization, (fs) (between)	0.101*** (0.006)	0.097*** (0.007)			0.009 (0.008)	0.012 (0.008)		
Knowledge-intensive regions, dummy (between)			0.362*** (0.011)	0.352*** (0.011)			–0.003 (0.013)	0.010 (0.014)
Resource specialized regions, dummy (between)			0.220*** (0.017)	0.223*** (0.018)			0.041* (0.020)	0.048* (0.021)
Knowledge intensity × AL, (between)	0.028 (0.018)	0.014 (0.012)			–0.035 (0.022)	–0.035* (0.014)		
Social inequality × AL (between)	–0.167*** (0.037)	–0.086*** (0.024)			0.037 (0.046)	0.009 (0.030)		
Labour market informality × AL (between)	0.066 (0.064)	0.097** (0.038)			0.127 (0.079)	–0.002 (0.046)		
Resource specialization × AL (between)	0.089* (0.039)	0.061** (0.023)			–0.008 (0.048)	–0.025 (0.028)		
Knowledge-intensive regions × AL (between)			0.026 (0.058)	0.078* (0.039)			–0.088 (0.070)	–0.142** (0.047)

(Table continues on the next page.)

(Continued.)

Variables	Log of hourly wage				Job satisfaction			
	factor scores interaction		regional clusters interaction		factor scores interaction		regional clusters interaction	
	non-formal	self-learning	non-formal	self-learning	non-formal	self-learning	non-formal	self-learning
Resource specialized regions × AL (between)			0.250* (0.100)	0.093 (0.063)			–0.057 (0.120)	–0.085 (0.075)
Number of observations	59,809	59,809	59,809	59,809	59,809	59,809	59,809	59,809
Log likelihood	–50,600	–50,600	–51,000	–51,000	–74,750	–74,740	–74,800	–74,790
Wald chi square	18,131***	18,151***	17,131***	17,142***	2,202***	2,216***	2,099***	2,107***

Note: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Third, the moderating between-individual effects of the regional environment on the relation between AL and labour market outcomes are significant. Resource regions provide effective platforms for non-formal work-related training, yielding a relative increase in earnings. Knowledge-intensive and more liberal market models offer advantages primarily for self-training initiatives. Self-training leads to a relative decrease in job satisfaction by 14% in the first year after training among residents of knowledge-intensive regions characterized by competitive labour markets. Moreover, the return on non-formal education in terms of perceived respect is 37% lower in these regions compared to others. In regions with high social inequality, the effects of non-formal and formal training on earnings are significantly lower (moderation effects μ are negative for wages), while informality in labour markets provides a little advantage in self-learning in terms of wages, and also strengthens trust in colleagues relative to other regions.

Table 5

Hybrid model estimations for trust in colleagues and perceived respect

Variables	Trust in colleagues				Perceived respect			
	factor scores interaction		regional clusters interaction		factor scores interaction		regional clusters interaction	
	non-formal	self-learning	non-formal	self-learning	non-formal	self-learning	non-formal	self-learning
AL, non-formal (within)	0.032 (0.017)	0.022 (0.014)	0.007 (0.017)	0.024 (0.014)	–0.001 (0.032)	–0.015 (0.025)	–0.037 (0.032)	–0.012 (0.025)
AL, self-learning (within)	–0.015 (0.011)	0.008 (0.013)	–0.015 (0.011)	–0.018 (0.013)	0.033 (0.019)	0.060* (0.023)	0.030 (0.019)	0.016 (0.023)
Knowledge intensity, (fs) (within)	0.030* (0.013)	0.031* (0.013)			0.043 (0.023)	0.043 (0.023)		
Social inequality, (fs) (within)	0.016 (0.012)	0.015 (0.012)			0.049* (0.021)	0.052* (0.022)		
Labour market informality, (fs) (within)	0.042** (0.014)	0.041** (0.015)			0.063* (0.026)	0.061* (0.026)		
Resource specialization, (fs) (within)	0.024 (0.015)	0.018 (0.015)			0.013 (0.026)	0.008 (0.027)		
Knowledge-intensive regions, dummy (within)			0.044 (0.028)	0.049 (0.028)			–0.089 (0.050)	–0.083 (0.050)
Resource specialized regions, dummy (within)			0.002 (0.023)	–0.006 (0.024)			–0.101* (0.041)	–0.117** (0.042)
Knowledge intensity × AL, (within)	0.005 (0.009)	–0.011 (0.007)			–0.005 (0.016)	–0.009 (0.012)		
Social inequality × AL (within)	–0.008 (0.017)	0.000 (0.013)			0.028 (0.031)	–0.004 (0.023)		
Labour market informality × AL (within)	0.048 (0.030)	0.015 (0.021)			0.122* (0.055)	0.066 (0.038)		
Resource specialization × AL (within)	0.028 (0.018)	0.056*** (0.013)			–0.002 (0.034)	0.040 (0.024)		
Knowledge-intensive regions × AL (within)			0.034 (0.028)	–0.014 (0.022)			0.077 (0.050)	0.013 (0.040)
Resource specialized regions × AL (within)			0.043 (0.044)	0.073* (0.033)			–0.014 (0.080)	0.117 (0.060)
AL, non-formal (between)	–0.057 (0.042)	–0.094** (0.035)	–0.104* (0.045)	–0.084* (0.035)	0.449*** (0.087)	0.367*** (0.072)	0.564*** (0.094)	0.396*** (0.072)
AL, self-learning (between)	–0.020 (0.023)	0.008 (0.028)	–0.023 (0.023)	–0.031 (0.028)	–0.176*** (0.047)	–0.117* (0.056)	–0.196*** (0.048)	–0.178** (0.059)

(Table continues on the next page.)

(Continued.)

Variables	Trust in colleagues				Perceived respect			
	factor scores interaction		regional clusters interaction		factor scores interaction		regional clusters interaction	
	non-formal	self-learning	non-formal	self-learning	non-formal	self-learning	non-formal	self-learning
Knowledge intensity, (fs) (between)	–0.003 (0.004)	–0.003 (0.004)			–0.095*** (0.007)	–0.100*** (0.008)		
Social inequality, (fs) (between)	–0.015* (0.007)	–0.014 (0.008)			0.140*** (0.015)	0.152*** (0.016)		
Labour market informality, (fs) (between)	0.057*** (0.012)	0.048*** (0.012)			0.172*** (0.023)	0.157*** (0.025)		
Resource specialization, (fs) (between)	0.002 (0.007)	0.001 (0.008)			0.195*** (0.015)	0.180*** (0.016)		
Knowledge-intensive regions, dummy (between)			–0.025* (0.013)	–0.026* (0.013)			–0.003 (0.026)	–0.015 (0.027)
Resource specialized regions, dummy (between)			–0.013 (0.019)	–0.009 (0.020)			0.377*** (0.039)	0.357*** (0.041)
Knowledge intensity × AL, (between)	–0.018 (0.020)	–0.010 (0.014)			–0.047 (0.042)	0.013 (0.027)		
Social inequality × AL (between)	0.005 (0.042)	–0.001 (0.028)			–0.086 (0.087)	–0.150** (0.057)		
Labour market informality × AL (between)	0.106 (0.073)	0.106* (0.043)			–0.026 (0.149)	0.108 (0.088)		
Resource specialization × AL (between)	0.053 (0.044)	0.026 (0.026)			–0.129 (0.091)	0.062 (0.054)		
Knowledge-intensive regions × AL (between)			0.034 (0.065)	0.023 (0.044)			–0.373** (0.135)	–0.083 (0.090)
Resource specialized regions × AL (between)			0.098 (0.109)	0.016 (0.070)			–0.349 (0.230)	0.012 (0.145)
Number of observations	59,809	59,809	59,809	59,809	59,809	59,809	59,809	59,809
Log likelihood	–61,300	–61,290	–61,330	–61,330	–109,700	–109,700	–109,900	–109,900
Wald chi square	403***	420***	347***	351***	1,675***	1,673***	1,333***	1,326***

Note: * p<0.05, ** p<0.01, *** p<0.001.

Robustness and heterogeneity

Robustness testing ensures that the results are not sensitive to specific modeling choices, sample restrictions, or variable definitions. First, we test the robustness of regional variables. At the factor analysis stage, we apply alternative factor rotation methods (varimax and equimax), which show comparable results in terms of factor loadings and the composition of observed variables within each factor. Additionally, while the differences between the first and second clusters are statistically insignificant for several indicators, the overall cluster composition remains stable. Factor analysis robustness allows for meaningful interpretation in terms of the institutional characteristics of regional economies, supported by the related literature. Second, in the regression models, we introduce both factor scores, capturing variations in regional economic models of resource distribution, and cluster membership indicators. Comparing models using factor scores with those using regional cluster dummies allows us to determine whether our findings depend on how regional economic regimes are measured and defined. Due to the nature of our sample, we can reliably differentiate between two clusters of regions: knowledge-intensive regions with more liberal and competitive labour markets, and resource-dependent, coordinated regions with more stable labour markets. As shown in Table 4 and Table 5, our results remain robust in terms of wages and job satisfaction across individuals, as well as trust in colleagues within individuals. Third, we test whether regional effects could be driven by omitted variables. To address potential confounding, we include theoretically relevant control variables in our models (e.g., educational attainment as a control for wages, and wages as a control for job satisfaction). Across both fixed effects and hybrid models, the inclusion of regional variables, whether as factor scores or cluster dummies, does not significantly impact the coefficients for control variables or AL, confirming the robustness of our main findings. Fourth, we examine the robustness of estimates across different age groups (25–39 and 40–64) and time periods, comparing results before and after the 2020 economic shock (see in Appendix Table A3). To ensure robustness, the effect of AL on wages, both within and between individuals, should remain stable across all groups. However, in some cases, AL exhibits varying effects for younger and older workers, suggesting heterogeneous returns to AL, depending on career stage.

Robustness tests confirm that some effects are both significant and robust. First, non-formal learning and self-learning have a robust direct impact only on wages and perceived respect between individuals. This suggests that the impact of AL within-individual career paths is typically isolated and subject to heterogeneity, consistent with previous research (Coelli–Tabasso 2019). For example, wage increases following AL are observed only for women, while men and adults over 40 years old exhibit no significant within-individual effects. However, the between-individual effects of AL remain robust, significant, and positive across all types of AL, suggesting wage premiums of 22–30% for individuals who participate in non-formal learning and 12–19% for those engaged in self-learning using internet resources. Additionally, non-formal learning positively influences perceived respect, whereas self-learning is associated with a decline in perceived respect.

Second, most regional effects measured by factor scores are robust. Regional variations in labour market outcomes can be largely attributed to differences in knowledge intensity, labour informality, social inequality, and resource specialization. Resource specialization and knowledge-intensive economic structures account for the most substantial differences in wages, job satisfaction, and perceived respect.

Third, the regional institutional environment plays a moderating role in the impact of AL on labour market outcomes. Several robust patterns emerge for knowledge-intensive, resource-dependent, and informal labour markets. Coordinated labour markets in resource-rich regions exhibit strong between-individual moderation effects, meaning that non-formal learning provided by local employers is associated with better returns in these environments. Knowledge-intensive regions show a robust and significant negative interaction between AL and job satisfaction for self-learning, suggesting that self-directed learning in these regions may not result in greater satisfaction due to the highly competitive environment and increased personal efforts required to acquire relevant knowledge. Informal labour markets tend to favor self-learning in terms of wage returns and enhance perceived respect for individuals who participate in non-formal AL.

Conclusion

The institutional environment of regions shapes human capital allocation strategies and influences the returns on investments in human capital. In this study, we examine how regional environments moderate the relationship between AL and various labour market outcomes, thereby demonstrating both monetary and non-financial returns on such investments for adults. Following the regional VoC framework, which suggests that diverse local configurations emerge over time within national market economies, we analyse 82 Russian regions over the period from 2013 to 2023. The findings reveal that regional economic models remain stable over time, sustaining distinct specializations that play a crucial role in the reproduction of human capital. Unlike previous studies, we enhance the quantitative measurement of regional variations in market economies by employing factor and cluster analyses. Further panel data regression analysis using hybrid models allows us to capture both within- and between-individual effects of the institutional environment, as well as its moderating role in the link between AL and labour market outcomes. Furthermore, in addition to traditional labour market outcomes such as salary and job satisfaction, the analysis also incorporates indicators of social capital and perceived respect.

The analysis allowed us to address the research questions formulated earlier. First, regional state-led market economies differ in their resource allocation regimes, particularly in terms of knowledge intensity, informality, inequality, and specialization. In this respect, the Russian economy resembles other state-led economies: within its coordinated model, where state influence is substantial, it differentiates between more liberal regions that foster technology-based, knowledge-intensive value creation, and resource-rich regions that generate key income streams and are subject to tight control through enhanced coordination of education and labour market policies. This finding aligns with previous research on the regional context in Russia (Korshunov et al. 2023). Our study also demonstrates that, within the context of a state-led economy, traditional formal indicators of the institutional environment, such as minimum wage levels, unionization rates, and regulatory enforcement, do not sufficiently explain regional differentiation. Rather, we selected indicators of knowledge intensity, informality, entrepreneurial activity, and resource and industrial specialization to better capture local institutional configurations in terms of distinct production models. As a result, we identified five types of regions that reflect the heterogeneity within the national market model.

Second, both AL and regional market economy characteristics impact labour market outcomes, such as wages, job satisfaction, trust in colleagues, and perceived respect. We explain these differences using regression analyses with hybrid models. The within-individual effects capture how AL and regional differences influence an individual's career trajectory over time within the RLMS panel, while the between-individual effects allow us to compare labour market outcomes across different individuals. Non-formal learning and self-learning show a robust direct effect on wages and perceived respect within individual career trajectories. However, these effects are heterogeneous; for example, only women experience significant wage increases after engaging in AL, and older cohorts exhibit no significant within-individual benefits from AL, corresponding to previous literature regarding uncertain economic returns associated with AL (Coelli–Tabasso 2019). Across individuals, all types of AL are associated with robust, positive outcomes. Individuals participating in non-formal learning experience wage premiums of 22–30%, while those engaged in online self-learning receive premiums of 12–19%. Non-formal learning is linked to higher perceived respect, whereas self-learning appears to reduce perceived respect. The regional institutional environment captured through factor scores that reflect knowledge intensity, labour informality, social inequality, and resource specialization also has a robust influence on labour market outcomes. Knowledge-intensive regions tend to have more liberal, competitive labour markets and are associated with dynamic economic opportunities. Regions that are resource-dependent and characterized by a more coordinated environment tend to have stable labour markets.

Finally, we showed that the effect of AL on both within- and between-individual labour market outcomes varies across different market economy regimes in regional contexts. The regional institutional environment moderates the impact of AL on labour market outcomes. For instance, coordinated environments in resource-dependent regions enhance the between-individual returns on non-formal learning, resulting in better wage outcomes when employers provide non-formal training. In contrast, knowledge-intensive regions exhibit a significant negative interaction between self-learning and job satisfaction, suggesting that the benefits of AL may be context-dependent. In informal labour markets, self-learning is particularly favored in terms of wage returns, while non-formal learning appears to better increase perceived respect.

Theoretical implications. Our research supports and extends the regional VoC framework by demonstrating that the returns on AL are significantly influenced by local institutional environments. Regional dimensions in human capital research are explored, providing insights into levels of knowledge intensity, resource dependence, and labour market informality to better explain variations in economic outcomes of AL. The results indicate that within-individual (dynamic) and between-individual (cross-sectional) returns to AL differ, suggesting that the benefits of AL are heterogeneous: demographic and regional factors contribute to these differences, and theoretical models need to account for the supply and institutional-related demand characteristics of human capital, including monetary (wages) and non-monetary (satisfaction, social capital, and empowerment) outcomes. Moreover, the influence of state-led market economy models is expected to expand in the context of recently observed waves of geoeconomic fragmentation (Alami 2023), allowing for the maintenance of various sub-models with varying levels of coordination and liberalization within a single national economy.

Policy implications. Hybrid models offer a powerful tool for informing policy. On the one hand, the within-individual effects revealed by these models provide insights into how individual development pathways evolve over time. On the other hand, the between-individual effects demonstrate broader structural differences across populations and regions. Therefore, policies promoting AL in the case of state-led market economies should be designed with regional contexts in mind. In knowledge-intensive, liberal-type regions, for example, enhancing access to self-directed learning and continuous skill development could maximize wage gains. In contrast, resource-dependent, coordinated-type regions may benefit more from non-formal, employer-provided training that aligns with stable labour market structures. Given the heterogeneous effects observed, such as significant wage increases for women but not for older workers, policies should include interventions that address the specific needs and barriers faced by different demographic groups, involving specialized training programs or incentives aimed at older workers and other vulnerable population groups. The dual impact of AL on financial and non-financial outcomes implies that workforce development policies should adopt a holistic approach to improving regional institutional quality that can increase the returns on AL.

Limitations and further research. The RLMS sample does not fully capture the diversity of regional contexts across Russia. Some regions are not represented, thus limiting the generalizability of the results. Additionally, factor scores and cluster classifications, while informative, may oversimplify the complex, multidimensional nature of regional institutional environments. In our study, we supplemented these measures with supporting evidence and descriptions from the literature. Finally, the scope of the research measurement is limited, as we only focus on wages, job satisfaction, and perceived respect, potentially omitting other relevant outcomes. The rationalization of AL, particularly the distinctions between non-formal learning and self-learning, may not fully capture the quality, intensity, or duration of the learning activities. Future studies should incorporate additional data sources, including administrative data, to overcome the lack of official statistics on labour market relations in the institutional environment. The study exploits limited quantitative indicators, which demonstrate the indirect effects of the chosen coordination models. It is also promising to include a broader set of outcomes, such as career advancement and employment stability, to provide a comprehensive institutional perspective on the returns on investment in AL.

Acknowledgments

The study was supported by the Russian Science Foundation, Grant No. 23-78-10165.
https://rscf.ru/project/23-78-10165/

Appendix

Table A1

Descriptive statistics for clusters

Regional indicators	All regions		1 – Neutral regions		2 – Redistri-butive-dependent		3 – Knowledge-intensive		4 – Natural resource speciali-zation		5 – Informal markets	
	M.	S.D.	M.	S.D.	M.	S.D.	M.	S.D.	M.	S.D.	M.	S.D.
GRP per capita in 2016 RUB, thousands	514	661	367	122	340	138	594	305	1401	1404	153	38
Number R&D personnel per 1,000 population	2.6	3.1	2.2	1.4	1.7	1.5	11.5	3.5	1.4	1.1	0.4	0.2
R&D total expenses in 2016 RUB, share of GRP, %	0.7	0.9	0.7	0.4	0.5	0.5	3.1	1.3	0.2	0.2	0.2	0.1
Property income, % of total income	3.3	1.9	3.2	1.1	3.3	1.5	6.2	3.5	2.6	0.9	0.3	0.2
Gini index	0.38	0.02	0.38	0.02	0.36	0.01	0.39	0.02	0.40	0.02	0.37	0.02
Social subsidies, % of total households' income	23.1	5.0	21.5	3.2	26.5	3.7	18.1	4.4	19.3	3.7	24.3	8.2
Unemployed per one vacancy	3.2	16.3	0.8	1.1	1.2	1.9	0.6	0.6	0.8	0.6	59.5	61.4
Government expenditure, % of GRP	21.8	10.9	17.5	4.7	25.0	11.2	16.3	3.1	20.7	13.5	39.6	15.9
Informal labour share, % of employed	13.5	5.3	14.8	4.0	12.9	3.9	8.4	4.0	10.7	4.2	28.7	4.9
Small and entrepreneurial business employment, %	23.2	6.9	23.6	3.8	22.5	5.4	27.8	5.7	24.5	12.1	11.7	3.1
Share of unprofitable organizations	32.5	6.7	28.6	4.7	34.5	6.1	29.4	4.0	38.6	6.8	29.9	6.8
Share of natural resource production in GRP	10.3	16.6	5.7	8.2	4.9	7.8	3.7	7.9	42.3	18.9	1.1	0.7
Share of industrial sector in GRP, %	0.3	0.1	0.3	0.1	0.3	0.1	0.3	0.1	0.2	0.1	0.2	0.0
Unemployment rate, %	6.1	4.0	5.3	2.0	6.1	3.0	3.9	1.9	5.7	2.1	19.4	8.9
Labour union participation, %	2.3	2.1	2.3	2.3	2.5	1.9	1.4	0.9	2.6	2.5	0.7	1.1
Number of region-years (median number of regions in a cluster)	902 (82)		300 (27)		367 (34)		72 (6)		129 (12)		34 (3)	

Note: M. = mean; S.D. = standard deviation.

Table A2

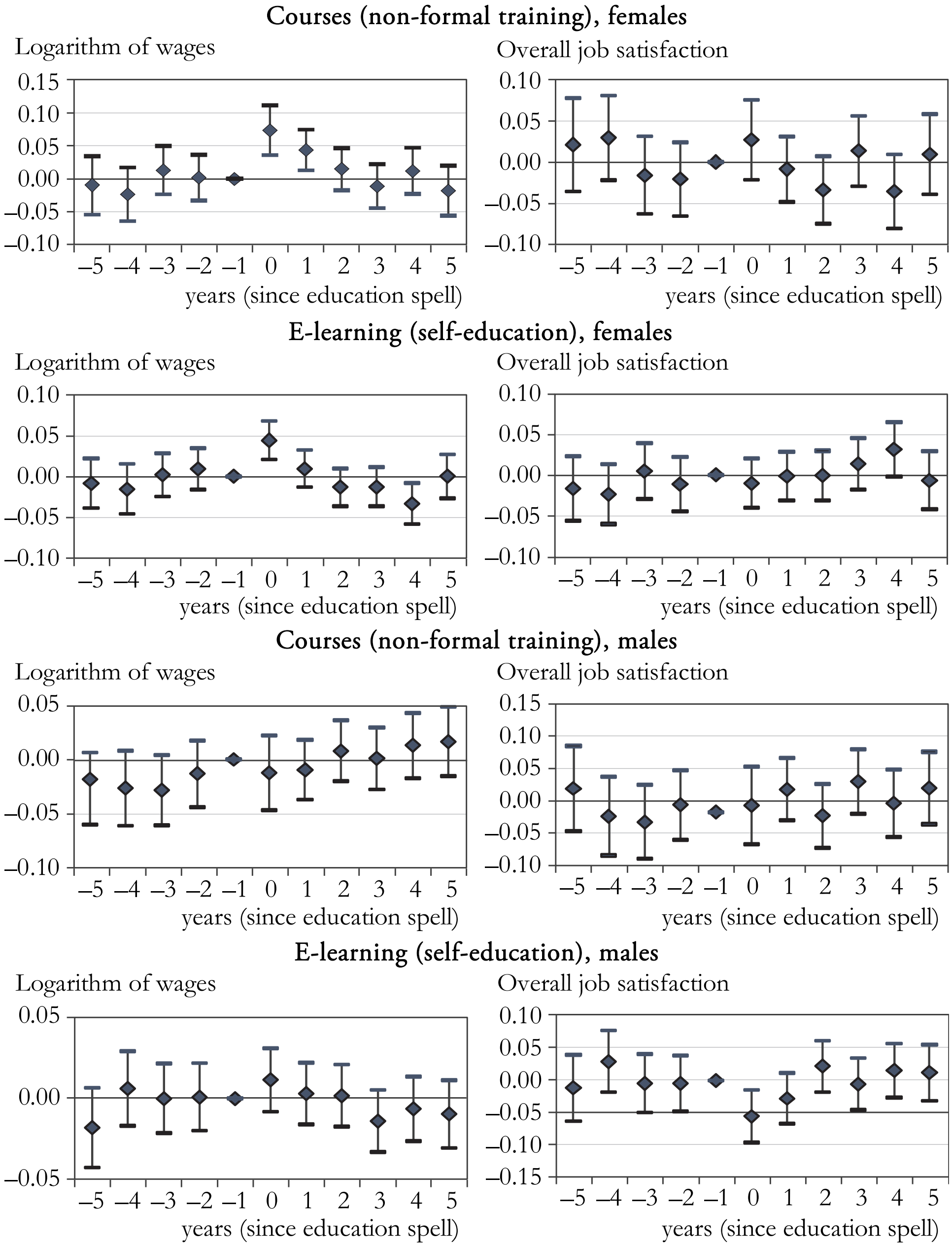
Descriptive statistics for the RLMS sample

Variables	Males		Females	
	M.	S.D.	M.	S.D.
Age, years	41.87	10.89	40.53	10.71
Log of wages	10.44	0.61	10.11	0.76
Job satisfaction, 5-point scale	3.75	0.83	3.79	0.85
Satisfaction with career opportunities, 5-point scale	3.32	1.06	3.36	1.08
Trust to managers, 5-point scale	3.72	0.91	3.80	0.91
Trust to colleagues, 5-point scale	3.97	0.73	4.00	0.75
Perceived power and control over life, 9-point scale	4.35	1.59	4.25	1.56
Perceived social respect, 9-point scale	6.43	1.52	6.47	1.54
Opportunity to find a better job, 5-point scale	3.04	1.20	2.92	1.25
Fear of losing a job, 5-point scale	3.54	1.25	3.52	1.29
Managers, dummy	0.24	0.43	0.21	0.40
Government organization, dummy	0.34	0.47	0.52	0.50
Entrepreneurs, dummy	0.04	0.19	0.02	0.14
Educational attainment, years	13.32	2.15	13.91	1.96
Experience, years	20.11	10.12	21.08	10.32
Language proficiency, 5-point scale	1.51	1.01	1.59	1.06
Married, dummy	0.19	0.39	0.16	0.36
Number of children under 18 years old	1.32	0.99	1.43	0.90
Health self-assessment, 5-point scale	3.53	0.59	3.40	0.58
Adult learning within last 12 months, courses, dummy	0.04	0.20	0.08	0.27
Adult learning within last 12 months, self-learning, dummy	0.10	0.30	0.15	0.36
Manufacturing, dummy	0.40	0.49	0.17	0.38
Army, police or national security, dummy	0.08	0.28	0.03	0.17
Engineering profession, dummy	0.17	0.38	0.05	0.22
Financial profession, dummy	0.05	0.21	0.17	0.38
ICT-related profession, dummy	0.04	0.20	0.01	0.10
Knowledge intensity, factor score	0.71	1.64	0.71	1.63
Social cohesion, factor score	0.26	0.84	0.24	0.84
Labour market informality, factor score	–0.14	0.47	–0.15	0.48
Resource specialization, factor score	–0.20	0.76	–0.18	0.76
Knowledge-intensive regions, dummy	0.28	0.45	0.27	0.45
Resource specialized regions, dummy	0.09	0.29	0.10	0.30
Number of observations	26,503		33,306	
Number of individuals (groups)	6,186		7,171	

Note: M. = mean; S.D. = standard deviation.

Figure A1

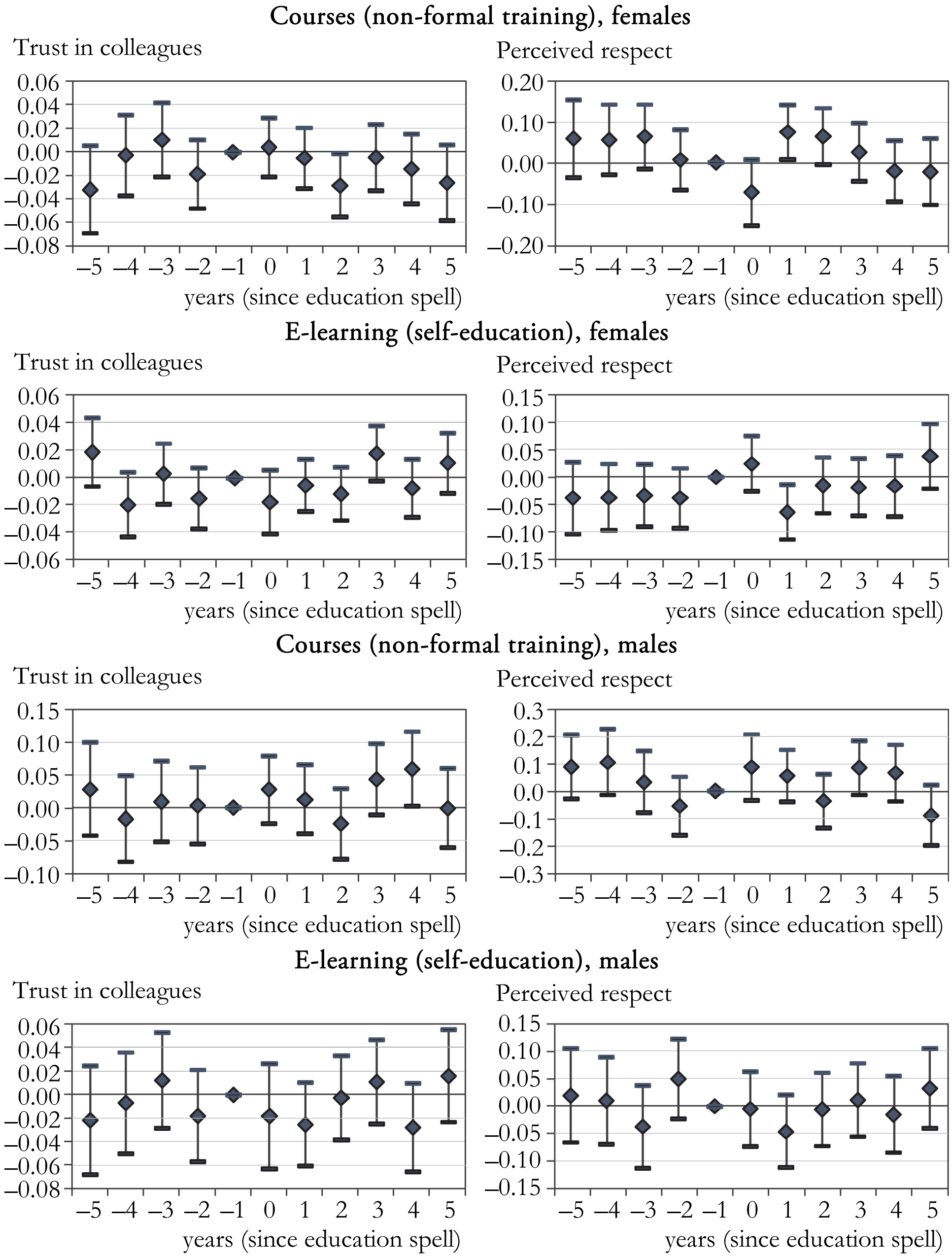
Conditional effects of AL on labour market outcomes (hourly log of wages and overall job satisfaction), estimated using model (1)



Note: dots signify coefficients before and after AL, vertical lines signify 95% confidence intervals for coefficients, considering individual fixed effects.

Figure A2

Conditional effects of AL on labour market outcomes (trust in colleagues and perceived respect), estimated using model (1)



Note: dots signify coefficients before and after AL, vertical lines signify 95% confidence intervals for coefficients, considering individual fixed effects.

Table A3

Results of robustness tests and heterogeneity analysis for all RLMS sample

Independent variables	Labour market outcomes			
	log of wage	job satisfaction	trust to colleagues	perceived respect
Non-formal AL, direct effect	pos. sig. within, except 40–64; pos. sig. between	n.s.	n.s. within, sig. neg. between for 25–39	n.s. within; pos. sig. between
Self-learning, direct effect	pos. sig. within, except 40–64; pos. sig. between	n.s.	n.s.	n.s. within; neg. sig. between
Knowledge intensity, direct effect	pos. sig. within; pos. sig between	pos. sig. within; n.s. between	pos. sig. within; n.s. between	n.s. within; neg. sig. between
Social inequality, direct effect	pos. sig. within; pos. sig between	n.s. within; neg. sig. between	n.s.	pos. sig. within; pos. sig. between
Labour market informality, direct effect	pos. sig. within; neg. sig. between	n.s. within; pos. sig. between	n.s. within; sig. pos. between	pos. sig. within for 25–39; pos. sig. between
Resource specialization, direct effect	n.s. within; pos. sig between	neg. sig. within; n.s. between	n.s.	n.s. within; pos. sig. between
Knowledge-intensive regions, direct effect	n.s. within; pos. sig. between	n.s.	n.s.	n.s.
Resource specialized regions, direct effect	n.s. within; pos. sig. between	pos. sig. within; pos. sig. between	n.s.	n.s. within; pos. sig. between
Knowledge intensity × AL	n.s.	n.s. within; neg. sig. between	n.s.	n.s.
Social inequality × AL	n.s. within, neg. sig. between for 25–39 and 2020–2023	n.s.	n.s.	n.s. within; neg. sig. between for 40–64 and 2013–2019
Labour market informality × AL	n.s. within; pos. sig. between for self-learning	n.s.	n.s. within; sig. pos. between for self-learning	pos. sig. within for non-formal AL; n.s. between
Resource specialization × AL	n.s. within; pos. sig. between for 40–64	n.s.	pos. sig. within for self-learning; n.s. between	n.s.
Knowledge-intensive regions × AL	neg. sig. within for self-learning for 2013–2019; n.s. between	n.s. within; sig. neg. between for self-learning	n.s.	n.s. within; neg. sig. between for 40–64 and 2013–2019
Resource specialized regions × AL	n.s. within; pos. sig. between for non-formal AL	n.s.	pos. sig. within for self-learning; n.s. between	n.s.

Notes: n.s.: not significant; pos.: positive; neg.: negative; sig.: significant effect; 40–64: age group from 40 to 64 years; 25–39: age group from 25 to 39 years (young adults). Robust results that are significant for all groups are highlighted in gray. Results subject to heterogeneity are highlighted in underlined text.

REFERENCES

ACEMOGLU, D.–ROBINSON, J. A.–VERDIER, T. (2017): Asymmetric growth and institutions in an interdependent world *Journal of Political Economy* 125 (5): 1245–1305. https://doi.org/10.1086/693038

ALAMI, I. (2023): Ten theses on the new state capitalism and its futures *Environment and Planning A: Economy and Space* 55 (3): 764–769. https://doi.org/10.1177/0308518X231156910

ALEXEEV, S. (2023): Technical change and wage premiums amongst skilled labour: evidence from the economic transition *Economics of Transition and Institutional Change* 31 (1): 189–216. https://doi.org/10.1111/ecot.12330

ALMEIDA, F.–MORAIS, J. (2024): Non-formal education as a response to social problems in developing countries *E-Learning and Digital Media* 22 (2): 1–17. https://doi.org/10.1177/20427530241231843

AVDEEVA, D. (2024): The contribution of human capital to economic growth in Russia *HSE Economic Journal* 28 (1): 9–43. https://doi.org/10.17323/1813-8691-2024-28-1-9-43

BASKAKOVA, M. E.–CHUBAROVA, T. V. (2021): Lifelong learning in Russia as a mechanism for the reproduction of human potential: gender aspect *Economic and Social Changes: Facts, Trends, Forecast* 14 (4): 169–184.

BECKER, G. S. (1993): *Human capital: a theoretical and empirical analysis with special reference to education, third edition* The University of Chicago Press.

BEGEN, N.–ATASOY, H. (2024): Technological literacy and employment: an inquiry into the adoption of learning technologies *Telecommunications Policy* 48 (10): 102864. https://doi.org/10.1016/j.telpol.2024.102864

CERAMI, A. (2009): Socio-economic transformations in post-communist countries: Central and Eastern Europe and Russia compared *Romanian Journal of Political Science* 9 (2): 25–41.

CHERNINA, E.–GIMPELSON, V. (2023): Do wages grow with experience? Deciphering the Russian puzzle *Journal of Comparative Economics* 51 (2): 545–563. https://doi.org/10.1016/j.jce.2023.01.005

COELLI, M.–TABASSO, D. (2019): Where are the returns to lifelong learning? *Empirical Economics* 57 (1): 205–237. https://doi.org/10.1007/s00181-018-1433-8

CROUCH, C.–SCHRÖDER, M.–VOELZKOW, H. (2009): Regional and sectoral varieties of capitalism *Economy and Society* 38 (4): 654–678. https://doi.org/10.1080/03085140903190383

DABROWSKI, M. (2023): Thirty years of economic transition in the former Soviet Union: microeconomic and institutional dimensions *Russian Journal of Economics* 9 (1): 1–32. https://doi.org/10.32609/j.ruje.9.104761

DESJARDINS, R. (2017): *Political economy of adult learning systems: comparative study of strategies, policies and constraints* Bloomsbury Academic.

EBNER, A. (2016): Editorial: exploring regional varieties of capitalism *Regional Studies* 50 (1): 3–6. https://doi.org/10.1080/00343404.2015.1039227

FEDOTOV, A. V.–LEBEDEV, K. V.–KOVALENKO, A. A.–POLUSHKINA, A. O. (2020): National projects and improvement of monitoring of their implementation in the sphere of lifelong vocational training *University Management: Practice and Analysis* 24 (1): 28–43. https://doi.org/10.15826/umpa.2020.01.002

FIELD, J. (2005): *Social capital and lifelong learning* University of Bristol. https://doi.org/10.1093/cdj/bsi107

GIMPELSON, V. E. (2022): Russian human capital in times of sanctions and counter-sanctions: some redistributive implications *Journal of the New Economic Association* 55 (3): 234–238. https://doi.org/10.31737/2221-2264-2022-55-3-16

GOUTHRO, P. A. (2022): Lifelong learning in a globalized world: the need for critical social theory in adult and lifelong education *International Journal of Lifelong Education* 41 (1): 107–121. https://doi.org/10.1080/02601370.2022.2033863

HALL, P. A.–SOSKICE, D. (2001): *Varieties of capitalism: the institutional foundations of comparative advantage* Oxford University Press. https://doi.org/10.5465/amr.2003.10196861

HAREN CONELY, L. M.–CORDIE, L. A. (2023): The learning democracy: the relationship between adult informal learning, lifelong learning mindset, and civic engagement *Adult Learning* 34 (3): 142–156. https://doi.org/10.1177/10451595231161345

HELLER-SAHLGREN, G. (2023): Lifelong learning and employment outcomes: evidence from Sweden *Education Economics* 31 (2): 189–210. https://doi.org/10.1080/09645292.2022.2059804

HERBRECHTER, D.–SCHEMMANN, M. (2022): Adult education research and neo-institutional theory. An introduction to the topic *International Yearbook of Adult Education 2022* 45 (1): 7–12. https://doi.org/10.3278/I72685W001

HINZ, J.–MONASTYRENKO, E. (2022): Bearing the cost of politics: consumer prices and welfare in Russia *Journal of International Economics* 137 103581. https://doi.org/10.1016/j.jinteco.2022.103581

HOLFORD, J.–BOYADJIEVA, P.–CLANCY, S.–HEFLER, G.–STUDENÁ, I. (2023): *Lifelong learning, young adults and the challenges of disadvantage in Europe* Springer International Publishing. https://doi.org/10.1007/978-3-031-14109-6

HOLFORD, J.–MICHIE, J. (2024): A permanent national necessity' – a manifesto for lifelong learning *International Review of Applied Economics* 38 (4): 386–394. https://doi.org/10.1080/02692171.2024.2367889

IOANNIDOU, A.–DESJARDINS, R. (2020): The political economy of adult learning systems *Zeitschrift Für Weiterbildungsforschung* 43 (2): 137–142. https://doi.org/10.1007/s40955-020-00166-z

JARVIS, P. (2004): *Adult education and lifelong learning: theory and practice (third edition)* RoutledgeFalmer (Taylor and Francis Group). https://doi.org/10.4324/9780203561560

JOHNSTON, D. W.–LEE, W. (2013): Extra status and extra stress: are promotions good for us? *ILR Review* 66 (1): 32–54. https://doi.org/10.1177/001979391306600102

KAPELIUSHNIKOV, R. I. (2023a): The Russian labor market: long-term trends and short-term fluctuations *Russian Journal of Economics* 9 (3): 245–270. https://doi.org/10.32609/j.ruje.9.113503

KAPELIUSHNIKOV, R. I. (2023b): The Russian labor market: a statistical portrait on the crises background *Voprosy Ekonomiki* 1 (8): 5–37. https://doi.org/10.32609/0042-8736-2023-8-5-37

KORSHUNOV, I. A.–SAFONOVA, M. Y.–SHIRKOVA, N. N.–CHAKHOYAN, G. A.–SZHENOV, E. S. (2020): Governmental support of lifelong learning at universities under the federal project "New opportunities for everyone" *University Management: Practice and Analysis* 24 (3): 90–104. https://doi.org/10.15826/umpa.2020.03.028

KORSHUNOV, I. A.–SHIRKOVA, N. N.–GORBUNOVA, M. L. (2023): Active participation of adults in continuing education: the role of regional economy and development of key industries *Economy of Regions* 19 (4): 1093–1109. https://doi.org/10.17059/ekon.reg.2023-4-11

LANE, D.–MYANT, M. (2007): *Varieties of capitalism in post-communist countries* Palgrave Macmillan UK. https://doi.org/10.1057/9780230627574

LUKYANOVA, A. L. (2011): Wage inequality in Russian economic transition (1991–2008): stylized facts and explanations *Journal of the New Economic Association* 1 (12): 124–147.

MARCZUK, A. (2024): Literature review of comparative school-to-work research: how institutional settings shape individual labour market outcomes *Journal for Labour Market Research* 58 (1): 19. https://doi.org/10.1186/s12651-024-00375-w

MASOURA, M.–MALEFAKI, S. (2023): Evolution of the digital economy and society index in the European Union: α socioeconomic perspective *TalTech Journal of European Studies* 13 (2): 177–203. https://doi.org/10.2478/bjes-2023-0020

NEYCHEVA, M.–BALTOV, M. (2024): Factors and obstacles determining the investments in continuing education and training of managers: the case of Bulgarian enterprises *European Journal of Training and Development* 48 (1/2): 1–22. https://doi.org/10.1108/EJTD-03-2022-0033

NÖLKE, A.–VLIEGENTHART, A. (2009): Enlarging the varieties of capitalism: the emergence of dependent market economies in East Central Europe *World Politics* 61 (4): 670–702. https://doi.org/10.1017/S0043887109990098

OSHCHEPKOV, A. Y. (2020): Interregional wage differentials in Russia: examining the role of long-term factors *Voprosy Ekonomiki* 1 (11): 86–112. https://doi.org/10.32609/0042-8736-2020-11-86-112

PABST, A. (2021): Rethinking evidence-based policy *National Institute Economic Review* 255 85–91. https://doi.org/10.1017/nie.2021.2

PINTO, H.–HEALY, A.–CRUZ, A. R. (2019): Varieties of capitalism and resilience clusters: an exploratory approach to European regions *Regional Science Policy and Practice* 11 (6): 913–933. https://doi.org/10.1111/rsp3.12183

PINTO LOPES, A. S. P.–RODRIGUES CARREIRA, P. M. (2020): Adult workers in higher education: enhancing social mobility *Education and Training* 62 (9): 1101–1117. https://doi.org/10.1108/ET-03-2018-0056

PRAKHOV, I. (2023): Indicators of higher education quality and salaries of university graduates in Russia *International Journal of Educational Development* 99 (May): 102771. https://doi.org/10.1016/j.ijedudev.2023.102771

PSACHAROPOULOS, G.–PATRINOS, H. A. (2004): Returns to investment in education: a further update *Education Economics* 12 (2): 111–134. https://doi.org/10.1080/0964529042000239140

REES, G. (2013): Comparing adult learning systems: an emerging political economy *European Journal of Education* 48 (2): 200–212. https://doi.org/10.1111/ejed.12025

RUHOSE, J.–THOMSEN, S. L.–WEILAGE, I. (2024): No mental retirement: estimating voluntary adult education activities of older workers *Education Economics* 32 (4): 440–473. https://doi.org/10.1080/09645292.2023.2229078

SAAR, E.–RÄIS, M. L. (2017): Participation in job-related training in European countries: the impact of skill supply and demand characteristics *Journal of Education and Work* 30 (5): 531–551. https://doi.org/10.1080/13639080.2016.1243229

SCHEMMANN, M.–HERBRECHTER, D.–ENGELS, M. (2020): Researching the political economy of adult learning systems. Theoretical amendments and empirical findings *Zeitschrift Für Weiterbildungsforschung* 43 (2): 259–273. https://doi.org/10.1007/s40955-020-00163-2

SCHRÖDER, M.–VOELZKOW, H. (2016): Varieties of regulation: how to combine sectoral, regional and national levels *Regional Studies* 50 (1): 7–19. https://doi.org/10.1080/00343404.2014.904040

SCHULTZ, T. W. (1961): Investment in human capital *American Economic Review* 51 (1): 1–17.

SCHUNCK, R.–PERALES, F. (2017): Within- and between-cluster effects in generalized linear mixed models: a discussion of approaches and the Xthybrid command *The Stata Journal: Promoting Communications on Statistics and Stata* 17 (1): 89–115. https://doi.org/10.1177/1536867X1701700106

SENGUPTA, N.–CHAWLA, N.–AGARWAL, A.–EVANS, J. (2023): Do online certifications improve job market outcomes? Evidence from an IT skills certification platform in India *Information Economics and Policy* 65 (December): 101067. https://doi.org/10.1016/j.infoecopol.2023.101067

SPENCE, M. (1973): Job market signaling *The Quarterly Journal of Economics* 87 (3): 355–374. https://doi.org/10.2307/1882010

STEVENS, A. H.–KURLAENDER, M.–GROSZ, M. (2019): Career technical education and labour market outcomes *Journal of Human Resources* 54 (4): 986–1036. https://doi.org/10.3368/jhr.54.4.1015.7449R2

TANDON, R.–SRINIVASAN, S. (2024): Learning from life: the value of everyday knowledge for empowerment and change *International Review of Education* 70 (2): 253–264. https://doi.org/10.1007/s11159-023-10057-3

THWE, W. P.–KÁLMÁN, A. (2024): Lifelong learning in the educational setting: a systematic literature review *The Asia-Pacific Education Researcher* 33 (2): 407–417. https://doi.org/10.1007/s40299-023-00738-w

WHALEN, C. J. (2022): *A modern guide to post-keynesian institutional economics* Edward Elgar Publishing. https://doi.org/10.4337/9781800885752

WOOLDRIDGE, J. M. (2021): Two-way fixed effects, the two-way Mundlak regression, and difference-in-differences estimators *SSRN Electronic Journal* 1–77. https://doi.org/10.2139/ssrn.3906345

ZEMTSOV, S. P.–VOLOSHINSKAYA, A. A. (2024): Russian regional resilience under sanctions *Journal of the New Economic Association* 3 (3(64)): 54–83. https://doi.org/10.31737/22212264_2024_3_54-83

ZHANG, J.–PECK, J. (2016): Variegated capitalism, Chinese style: regional models, multi-scalar constructions *Regional Studies* 50 (1): 52–78. https://doi.org/10.1080/00343404.2013.856514

ZOCH, G. (2023): Participation in job-related training: is there a parenthood training penalty? *Work, Employment and Society* 37 (1): 274–292. https://doi.org/10.1177/09500170221128692

ZUBAREVICH, N. V. (2022): Regions of Russia in the new economic realities *Journal of the New Economic Association* 55 (3): 226–234. https://doi.org/10.31737/2221-2264-2022-55-3-15

INTERNET SOURCES

FEDERAL STATE STATISTICS SERVICE [ROSSTAT] (2024a): *Regions of Russia. Socio-economic indicators 2024*. https://rosstat.gov.ru/folder/210/document/13204 (downloaded: December 2024)

FEDERAL STATE STATISTICS SERVICE [ROSSTAT] (2024b): *Statistical yearbook "Sustainable development goals in the Russian Federation" 2024*. https://rosstat.gov.ru/sdg/report/document/69771 (downloaded: December 2024)

FEDERAL STATE STATISTICS SERVICE [ROSSTAT] (2024c): *Microdata from sample labor force surveys 2023*. https://rosstat.gov.ru/storage/mediabank/bd_ors_2023.rar (downloaded: December 2024)

FEDERAL STATE STATISTICS SERVICE [ROSSTAT] (2024d): *Selective federal statistical observation of population participation in continuous education 2020 (microdata)*. https://rosstat.gov.ru/free_doc/new_site/population/trud/inobr2020/index.html (downloaded: February 2024)

HIGHER SCHOOL OF ECONOMICS (2024): *Russia longitudinal monitoring survey, RLMS-HSE*. https://www.hse.ru/en/rlms/downloads (downloaded: September 2024)

SIMOLA, H. (2024): Detecting irregularities in Russian economic statistics *BOFIT Policy Briefs* 1 (9): 1–18. https://publications.bof.fi/bitstream/handle/10024/53847/bpb924.pdf?sequence=1&isAllowed=y (downloaded: November 2024)