Evaluation of the impact of human capital on innovation activity in Russian regions

Valentina Teslenko a, Roman Melnikov b and Damien Bazin c

ABSTRACT
The article evaluates the impact of changes in the structure of human capital on the innovative activity of Russian regions. We hypothesize that the different types of human capital formed by vocational education and training, higher education and doctoral programmes play an independent and significant role in the process of innovative development. To test the hypotheses, data on the innovative product output, applications for international patents and the structure of human capital of Russian regions for the period 2009–18 are used. The results of the analysis indicate that the impact of growth in the share of employees with higher education on the innovation and patent activity in Russian regions is characterized by diminishing returns, the shortage of skilled workers with vocational education hinders the growth of innovation output, and the growth in the share of researchers with candidate or doctor of science degree increases innovation and patent activity if proper research and development funding is provided.

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INTRODUCTION

From a theoretical point of view, a high share of the educated population is important for the economic development of regions, as new technologies cannot be implemented without skilled labour and developed or adapted without the involvement of highly qualified researchers (Acemoglu & Autor, 2012; Nelson & Phelps, 1966; Schultz, 1975). The high importance of human capital as a factor of innovative development at the regional level is based on both theoretical (Cooke, 2001; Grossman & Helpman, 1994) and empirical (Diebolt & Hippe, 2019; Felsonstein, 2015; Grözinger et al., 2017; Pater & Lewandowska, 2015) studies using data from...
regions around the world. However, heterogeneity in the impacts of different types of human capital on regional innovation and patent activity remains unexplored in relation to economies that have undergone economic transformation in recent decades and have had to restructure their innovation systems in the face of a transition to a market economy. This study is an attempt to fill this gap.

Russia seems an interesting object for studying this issue. On the one hand, the human capital of Russian regions is higher than in most countries of the world, because in 2019 Russia had the third highest percentage of people with higher education after South Korea and Ireland: 62% compared with 45% of the Organisation for Economic Co-operation and Development (OECD) average (for the population aged 25–35 years) (OECD, 2020). On the other hand, parallel to the expansion of higher education, the numbers of doctoral programme graduates and researchers with candidate or doctor of science degrees are decreasing. In 1998, 16.6 researchers with candidate or doctor of science degrees were accounted for per 10,000 employees in Russia, but in 2018 this figure decreased to 14.0. Therefore, to measure the human capital of regions, a more comprehensive system of indicators is needed than just the share of employees with higher education, which is used as the only indicator of human capital in many empirical studies, but can create misconceptions about the level of human capital in regions and the possibilities of its use for innovative development. In addition, the Russian economy is characterized by significant interregional imbalances, and among the 85 regions forming it there are both some regions that implement the model of innovative development with relative success and regions with low and extremely low levels of innovation activity, which allows us to investigate the impact of human capital on innovation in a fairly heterogeneous environment.

In this article we modify and develop the approach of Crescenzi and Jaax (2017) to analyse the results of innovative development of Russian regions. Crescenzi and Jaax mainly focus on the role of regional research and development (R&D) on patenting using augmented knowledge-production function. We concentrate on the impact of different types of human capital on innovation activity of regions.

First, unlike Crescenzi and Jaax, who used only one indicator of the human capital of regions (the share of employees with higher education), we use three indicators: the share of employees with vocational education and training, the share of employees with higher education, and the share of researchers with candidate or doctor of science degrees in the total number of employees, hypothesizing that the impact of these variables on the results of innovative development of regions may be non-linear. This approach has revealed a more significant impact of human capital on the innovative development of Russian regions, primarily due to the researchers with candidate or doctor of science degrees. Second, as the main dependent variable, we consider innovative product output, which reflects the market success of the development of new products and technologies. We hypothesize that the opportunities for the manufacturing of innovative products and provision of innovative services depend on the provision of regions with skilled workers with vocational education and training, which may be reduced as a result of the expansion of higher education; this hypothesis is confirmed by empirical analysis. Third, we investigate the moderating role of R&D funding on the effect of human capital of researchers with candidate of science or doctor of science degree and demonstrate a positive moderating effect of R&D funding in the relationship between human capital and regional innovation performance. Fourth, unlike Crescenzi and Jaax, we evaluate the impact of new educational policy tools implemented after the global crisis of 2008, namely, the programmes of national research universities, flagship universities, and the dual model of vocational education and training development. Crescenzi and Jaax evaluated the impact of the tools of the scientific and technical policy of the Soviet period, such as the foundation of scientific and defence industrial cities.

The estimation results have revealed a more significant impact of human capital on the innovative development of Russian regions in comparison with the estimates of Crescenzi and Jaax,
primarily due to the variable of researchers with candidate or doctor of science degrees. The impact of growth on the share of employees with higher education on the innovation and patent activity in Russian regions is characterized by diminishing returns, and the shortage of skilled workers with vocational education and training is a rather serious limitation that restrains the increase in the manufacturing of innovative products and provision of innovative services. Both the negative trend towards a reduction in the number of researchers with candidate or doctor of science degrees and the low level of R&D funding reduce the return on human capital concentrated in the R&D sector of Russian regions. While the establishment of a national research university in a region and a region’s participation in the dual model of vocational education and a training development programme do not have a statistically significant impact on the increase in innovative product output in the short run, the availability of these elements of the regional education system allows us to expect greater innovation in the long run.

LITERATURE REVIEW AND HYPOTHESIS

The models of endogenous growth theory (Acemoglu, 1996; Aghion & Howitt, 1990; Lucas, 1988; Romer, 1990) attach particular importance to human capital as a factor of innovative economic development.

The Romer (1990) model disaggregates the economy into three main sectors: the R&D sector, the intermediate products sector and the end-user sector. The knowledge production function that determines the performance of the R&D sector is described by an equation

\[ \dot{A} = \delta A H_A, \]

where \( A \) is a stock of scientific knowledge; \( H_A \) is the human capital used by the R&D sector; and \( \delta \) is the parameter of R&D productivity. The endogenous growth of the economy in the Romer model is the result of an increase in the stock of knowledge \( A \) and, as a result, an increase in the productivity of human capital employed in the R&D sector. The model shows that innovative product output should increase as the share of qualified researchers engaged in R&D in the overall structure of employment increases. At the same time, the model does not take into account that the capabilities of researchers and their results vary significantly depending on access to funding.

In the Griliches (1979) model the knowledge production function is defined as a function of the R&D expenditure of previous periods:

\[ K_t = a_0 [W(B)R_t]^{\mu t + \nu}, \]

where \( K_t \) is knowledge at the moment \( t \); \( W(B)R_t \) is the function of the lagged R&D expenditure; \( \mu t \) is the trend; and \( \nu \) is random noise. This model has become a popular tool for empirical analysis because of its simplicity and the availability of data to estimate it, but its significant drawback is the lack of a separate variable of human capital because R&D expenditure cannot produce results without R&D staff capable of rationally and creatively solving research and innovation problems.

The Brenner and Broekel (2011) model describes the factors of regional innovation activity with an emphasis on human capital. The expected productivity of the innovator in this model is set by an equation:

\[ E(I) = \eta_i(c_i, F_i), \]

where \( c_i \) is the individual characteristics of the researcher \( i \); and \( F_i \) is regional-level factors. The number of innovators \( G_s \) in the region \( s \) is determined by the attractiveness factors \( A_s \) of the region \( s \) for researchers. Therefore, the expected innovation output of the region is defined as:

\[ E(I) = \sum_{i=1}^{G_s(A)} \eta_i(c_i, F_s). \]
The knowledge production function of Charlot et al. (2015) is based on the factors of the innovative process at the micro-level and on additional regional mechanisms, such as spatial spillovers of knowledge and agglomeration economies:

\[ K_{r,t} = g(RD_{r,t}, HK_{r,t}, WRD_{r,t}, WHK_{r,t}, ur_{r,t}), \]

where \( K_{r,t} \) is the regional patent activity; \( g \) is some function (we use the Cobb–Douglas production function); \( r \) is the index of the region; \( t \) is the index of time; \( RD_{r,t} \) is the regional R&D expenditure; \( HK_{r,t} \) is the regional human capital; \( WRD_{r,t} \) is the R&D expenditure in neighbouring regions; \( WHK_{r,t} \) is the human capital of neighbouring regions; and \( ur_{r,t} \) is the other factors. Educational training and the talent of individual innovators not only allow them to generate new ideas but also help them to gain knowledge from external sources. The ability to innovate depends on both the availability of human capital and the exchange of information through local and interregional networks.

Empirical studies using data from different countries around the world confirm the significant role of human capital as a factor of regional innovative development. Pater and Lewandowska (2015), using 18 indicators of 225 regions of the European Union (EU) for the period 2008–10, classified the EU regions into five homogeneous groups in terms of human capital and innovation activity. They concluded that the relatively low innovation activity of the economies of some EU regions is associated with underinvestment in human capital.

Felsenstein (2015) evaluated the impact of human capital on the innovation activity of Israeli regions using panel data from 2002 to 2010. Innovation activity was measured by the logarithm of R&D expenditure; and human capital by the average length of formal education and the share of highly educated immigrants (with a duration of education of over 16 years) in the total population. The estimations showed that the duration of a formal education had a positive and significant effect on innovation in Israeli regions, but the effect of the share of highly educated immigrants was negative.

Grözinger et al. (2017) investigated the impact of human capital on the patent activity of German regions. It was found that the proportion of employees with higher education had a significant positive effect on regional patent activity. Diebolt and Hippe (2019) found that human capital had a significant positive impact on both patent activity and economic growth in European regions in the long run.

Similar studies were carried out using data from Russian regions. Shtertser (2005) evaluated the impact of the number of researchers with candidate or doctor of science degrees on the number of applications for Russian patents. Regression based on panel data for 76 regions for the period 1998–2003 showed a significant negative effect of the number of researchers on patent activity, which, according to the author, indicates the low quality of human capital in the Russian R&D sector. However, the number of applications for Russian patents may not adequately reflect the results of scientific and technical activities due to the high proportion of approved applications and the low commercialization rate of patents (Crescenzi & Jaax, 2017; Zemtsov et al., 2016). In addition, Shtertser (2005) did not take into account that the return on human capital may increase as R&D funding increases.

Considering the shortcomings of Russian patents, Crescenzi and Jaax (2017) used the number of patent applications registered under the Patent Cooperation Treaty (PCT) as an indicator of the patent activity of Russian regions, as this type of patent protects rights outside the Russian Federation and involves a much more complicated process. Estimation results of panel regression with fixed effects based on data for the period 1997–2013 did not show a significant effect of the change in the share of employees with higher education on the patent activity of Russian regions. However, cross-sectional regression using the averages of variables for the
period 1997–2013 showed a significant positive effect of the share of employees with higher education on patent activity. It should be noted that Crescenzi and Jaax did not use the number of researchers with candidate or doctor of science degrees as a characteristic of human capital in the regions, which is a significant limitation of their study.

Zemtsov et al. (2016) investigated the dependence of the patent activity indicator of Russian regions, built as a weighted average of patent applications registered by Rospatent and filed under the PCT procedure, on the number of economically active citizens with higher education. The results of the estimation of panel regressions with fixed effects showed a significant positive effect of this independent variable on the patent activity of Russian regions.

The authors believe that the study of the impact of human capital on the results of innovative development of regions should be based on a classification of types of human capital performing different functions in the process of solving the problems of innovative development. From this point of view, the classification of Rasmussen (1983), who identified three main categories of workers depending on the importance of their competencies for the challenges of innovative development, is of interest. These categories include:

- Workers competent in the ‘skill’ category. More than 50% of these workers’ tasks are typical tasks, mainly in the field of physical labour.
- Workers competent in the ‘rule’ category. More than 50% of the tasks of these employees are based on following instructions and performing procedures.
- Employees competent in the ‘knowledge’ category (holders of the highest quality human capital). More than 50% of the tasks of these employees require creativity, analytical work as well as the ability to perform in conditions of high uncertainty.

At the same time, Rasmussen’s classification does not align the qualifications of employees and the nature of the tasks they perform with the levels of formal education obtained. In theory, an employee with a higher level of formal education should be more qualified and more important in the process of innovation, so the classification of human capital should consider the levels of education at which it is formed. This classification allows one to determine rational proportions in the structure of human capital of regions corresponding to a certain level of technological and institutional development of the national economy and to identify scarce and excessive types of human capital in regions.

We propose to dissect three types of human capital depending on their role in the process of innovative economic development.

The first type of human capital corresponds to the level of mid-tier professionals who have the necessary skills and competencies to implement technological processes, including those of an innovational nature. This type of human capital is formed by practice-oriented vocational education and training programmes as well as in the course of occupational training. It plays a crucial role in the economies of such technologically advanced countries as Germany, Switzerland and Sweden.

The second type of human capital can be attributed to entrepreneurs and engineers, who do not develop new technologies but are engaged in their direct implementation into production processes. This type of human capital is formed by higher education programmes (bachelor’s and master’s degrees), but training in the workplace also plays an important role in the formation of this type of human capital. It should be noted that empirical studies using data from the United States (Sand, 2013) and China (Liang et al., 2016) have shown that the external effects of the expansion of higher education decrease as it becomes widespread. This dependence may also manifest itself in Russian conditions.

The third type of human capital is the human capital of researchers, which is formed at the level of doctoral programmes. This type of human capital determines the dynamics of economic...
development in the Romer (1990) model, but its effective use requires a favourable institutional environment, as well as adequate funding for R&D.

We put forward the following hypotheses about the impact of human capital on the innovative development of Russian regions:

**Hypothesis 1:** The first type of human capital, formed by vocational education and training programmes, is essential for the manufacturing of innovative products and provision of innovative services. The scarcity of this type of capital does not limit patent activity but creates barriers to the production of new types of products for the region.

**Hypothesis 2:** The return on human capital of the second type, formed by higher education programmes, decreases as higher education becomes widespread. The disruption of rational proportions in the structure of human capital and excessive increase in the share of employees with higher education via reducing the share of researchers with candidate or doctor of science degrees and workers with vocational education and training does not contribute to the growth of innovation activity.

**Hypothesis 3:** The return on human capital of the third type involved in R&D depends significantly on the amount of R&D funding and increases along with the growth of R&D funding.

**THE STRUCTURE AND DYNAMICS OF HUMAN CAPITAL OF RUSSIAN REGIONS**

The development of human capital of the three types identified above has been very uneven in Russia after the collapse of the Soviet Union and the transition to a market economy. The human capital of the second type has developed rapidly: while in 1992 the share of employees with higher education was 16.1%, in 2018 it rose to 34.2%. A steady trend towards an increase in the share of employees with higher education has been observed in all Russian regions (GKS, 2020).

In 1992, the median share of employees with higher education in Russian regions was 13.6%, and more than 25% of employees had higher education only in the cities of Moscow (35.3%) and St Petersburg (28.6%). However, in 2018 the median share of employees with higher education in Russian regions reached 31.4%, so the typical Russian region moved to the educational structure of employees which was characteristic of the cities of Moscow and St Petersburg as of 1992. The minimum share of employees with higher education of 23% was registered in the Jewish Autonomous Region, and in eight regions – the city of Moscow (49.7%), Yamalo-Nenets Autonomous Region (45.8%), Republic of North Ossetia – Alanya (44%), St Petersburg (43.5%), Sevastopol (43%), Karachay-Cherkess Republic (43.2%), Kalmykia (43.2%) and Moscow region (41%) – the share of employees with higher education exceeded 40%.

Formal indicators of the share of employees with higher education show a significant increase in the human capital of Russian regions achieved since the beginning of market reforms. However, the impact of this increase on socioeconomic development seems rather ambiguous, as it was achieved, according to Balatsky (2014), by ‘inflating the educational bubble’. With the number of Russian universities increasing 2.2 times and the number of students increasing 2.7 times between 1990 and 2008, in many cases, the provision of higher education acquired the characteristics of a trade in diplomas, unaccompanied by proper formation of professional skills and knowledge of graduates.

A similar position is taken by Grechko (2014), who believes that reforms of the Russian higher education system during the transition to a market economy have led to its degradation. In addition, due to unfavourable institutional conditions in the Russian economy, the most
talented entrants choose majors in law and public administration, focused on participation in the process of rent distribution, rather than science, technology, engineering and mathematics (Natkho & Polishchuk, 2012). This choice negatively affects prospects for innovative development.

In these conditions, the increase in the number of people with higher education has ceased to adequately reflect the increase in the human capital of the regions. In the following years, due to the reduction in the number of secondary school graduates, optimization of the number of universities and tighter regulation of their activities, this ‘educational bubble’ began to deflate, but the trend towards an increase in the proportion of employees with higher education continued due to a significant difference in the educational structure of demographic cohorts entering and leaving the labour market. At the same time, the question of whether Russian regions have been able to benefit from a fairly radical change in the structure of their human capital and whether this has contributed to an increase in innovation activity is of interest.

The share of employees with vocational education and training in the Russian economy as a whole has increased by 6 percentage points over the last 20 years (from 39% in 1998 to 45% in 2018). It peaked at 46.7% in 2010 and later slightly declined. The leaders in the share of employees with vocational education and training in 2018 were the Komi Republic (55.6%), Kostroma region (55.4%), and Tver region (55.4%). Vocational education and training have been least popular in Chechnya (13.9%) and Dagestan (21.3%). The Kursk region, Karamchay-Cherkess Republic and Penza region experienced the largest increase in the share of employees with vocational education and training in the period 1997–2018 (47.9%, 47.8% and 46.6%, respectively).

The tendency towards an increase in the share of holders of human capital of the first and second types was accompanied by another trend: a decrease in the share of holders of human capital of the third type. While in 1999 the Russian economy accounted for 136 people employed in R&D per 10,000 employees, in 2015 this fell to 95.5. Moreover, the process of reducing the number of researchers affected the majority of regions, but above all those with a high concentration of scientific potential.

The number of people with candidate or doctor of science degrees employed in R&D has also decreased. In 1998, there were 13.4 candidates of science working in R&D per 10,000 employees, but in 2018 this figure fell to 10.5. In the same year, the number of doctors of science working in R&D per 10,000 employees was 3.2. It then increased, peaking at 3.84 in 2012, but gradually dropped to 3.5 in 2018.

Moscow is the leader in the number of doctors of science employed in R&D. However, while in 1998, 19.8 doctors of science per 10,000 employees worked in Moscow’s research organizations, in 2018 their number decreased to 12.86, or by 60%.

The total number of researchers with candidate or doctor of science degrees per 10,000 employees has decreased from 16.6 in 1998 to 14.0 in 2018. In Moscow, the number of researchers with candidate or doctor of science degrees has halved over the last 20 years. These data convincingly testify to the declining prestige of the researcher’s work in Russia. Thus, parallel to the increase in the stock of human capital of the first and second types, Russia has been losing human capital of the third type, especially necessary for the development and implementation of new technologies.

The trend towards an increase in the share of the population with higher education is evident not only in Russia but also in the world economy. Although the 2007–09 financial crisis worsened the economic situation in many OECD countries, the higher education system continues to expand. In 2017, the OECD average proportion of people aged 25–34 years who have completed higher education has reached 44%, while nine OECD countries have exceeded the 50% level. The increase in the share of the population with higher education is also common in Asian countries, particularly India and China. The OECD predicts that the number of those aged 25–
34 years with higher education in OECD and G20 countries will increase from 137 million in 2013 to 300 million by 2030 (Sarrico, 2018).

However, the emphasis on higher education is not universal for all technologically advanced countries. Vocational education and training are more prevalent in Germany, Switzerland and Sweden, while higher education in these countries is considered ‘elite’ and emphasizes the training of engineers and researchers.

At the same time, the Russian tendency of reducing the number of thesis defences and candidate and doctor of science degrees awarded does not correspond to the international trend. In the United States, France and Finland, the number of people with a PhD degree increased by 20–30% between 2013 and 2018 (United Nations Educational, Scientific and Cultural Organization (UNESCO), 2019). In the OECD countries, the number of PhD degrees awarded annually increased by 56% from 2000 to 2012 (OECD, 2014). Unlike most countries of the world, Russia is reducing both the jobs for researchers with scientific degrees and the output of researcher training programmes, which can negatively affect the results of scientific, technical and innovation activities.

TOOLS OF RUSSIAN EDUCATIONAL POLICY AIMED AT STIMULATING INNOVATIVE DEVELOPMENT OF REGIONS

After the financial crisis of 2008, the Russian government has taken a series of measures to remove barriers to cooperation between participants in innovative processes and to form a Russian national innovation system (Gokhberg & Roud, 2012).

The state policy on the development of Russian higher education included special measures to stimulate innovation activity. Several universities were awarded special status. The status of national research universities has been granted to universities capable of generating knowledge and ensure the efficient transfer of technology to the economy; conduct a wide range of fundamental and applied research; and have highly efficient master’s training programmes and highly qualified personnel. In 2008, the status of national research universities was granted to the Moscow Institute of Engineering and Physics (State University) and the State University of Technology ‘Moscow Institute of Steel and Alloys’ by the decree of the President of the Russian Federation. In 2009 and 2010, 27 other leading Russian universities, representing different regions of the country, were granted the status of national research universities on a competitive basis. These universities receive priority funding from the state. If the university does not demonstrate compliance with its status, the Government of the Russian Federation has the right to deprive the university of the category of ‘national research university’ and to stop funding its programmes.

To promote the socioeconomic development of the Russian regions via the establishment of university centres for innovative, technological and social development of the regions, the Ministry of Education and Science of the Russian Federation launched the project ‘Development of a Network of Flagship Universities’ in 2015. In 2011, 11 flagship universities were selected as programme participants for the period up to 2020. The second stage of the competition was held in 2017, as a result of which the number of participants in the programme increased by 22.

In 2013, the Agency for Strategic Initiatives took the first steps to establish a dual vocational education and training system in Russian regions. Thirteen regions of Russia with successful experience in attracting investments took part in the pilot project. Public funding for the development of the dual vocational education and training model has been provided via parallel projects to strengthen public–private partnerships in vocational education and training.

Cluster policies can also have a significant impact on the prospects for innovation in the regions. The first strategic document that defined the foundations of cluster policy in the Russian Federation was the concept of long-term socioeconomic development of the Russian
Federation for the period up to 2020, which defined the creation of a network of clusters as a condition for modernizing the economy and realizing the competitive potential of the regions. In 2010, the Ministry of Economic Development and Trade of the Russian Federation established cluster development centres to promote cooperation between small and medium-sized enterprises (SMEs), educational and research institutions, government agencies and other stakeholders as part of the SME support programmes (Longhi & Rochhia, 2016). These clusters appeared in regions with high scientific potential, where science cities, closed administrative and territorial entities, and special economic zones were located. The pilot clusters specialize in the following strategic areas: nuclear power, aeronautics and space, shipbuilding, pharmaceuticals, biotechnology, medical devices, new materials, chemistry, information and communication technologies, and electronics.

It can be hypothesized that the formation of national research universities, flagship universities, the dual vocational education and training system, and innovative clusters has had a positive impact on the level of innovation and patent activity of Russian regions. In the second part of our empirical analysis, we will investigate the relationship between these educational policies and indicators of innovative development of regions.

**METHODS**

We specify the following 'augmented' knowledge production function that takes into account:

- the qualitative differences between different types of human capital (possessed by employees with vocational education and training, higher education and candidate or doctor of science degrees), each of which can play an independent and significant role in the process of innovative development;
- diminishing returns on certain types of human capital while disrupting the rational structure of human capital formed by educational programmes at different levels; and
- the dependence of the return on human capital of researchers with candidate or doctor of science degrees on the amount of R&D funding.

\[
I = b_0 + b_1 h_{c1} + b_2 h_{c2} + b_3 h_{c3} + b_4 h_{c1}^2 + b_5 h_{c2}^2 + b_6 h_{c3}^2 + b_7 r_d + b_8 \times \text{SL}(r_d),
\]

where \(I\) is the result of innovation activity which can be measured by the logarithm of the innovative products output or the number of patent applications filed; \(h_{c1}, h_{c2}\) and \(h_{c3}\) are the share of employees with vocational education and training, higher education and candidate or doctor of science degrees, respectively; \(r_d\) is the logarithm of R&D expenditure per employee; and \(\text{SL}(r_d)\) is the a spatial lag of logarithm of R&D expenditure per employee characterizing the possibility of knowledge spillover from neighbouring regions.

Spatial lags for each region are weighted averages of the corresponding variable in other regions (Anselin, 1988; Elhorst, 2014). We used a matrix of neighbourhood, elements of which \(w_{ij} = 1/a_i\) if regions \(i\) and \(j\) have common boundaries, where \(a_i\) is the number of regions with which the region \(i\) borders; and \(w_{ij} = 0\) if regions \(i\) and \(j\) do not have common boundaries or \(i = j\). The spatial lag of logarithm of R&D expenditure per employee was calculated as:

\[
\text{SL}(r_d) = \sum_{j=1}^{n} w_{ij} r_d.
\]

We used the innovative products output per 10,000 employees deflated by the consumer price index as the main dependent variable. In accordance with the methodology of the Russian State Statistic Service, innovative product output is calculated as the value of goods, works and services, new or technologically modified during the last three years. This indicator measures
innovations by the magnitude of market success from their production and demonstrates the ability of regional economies to master the production of innovative products and services.

We estimated the following specification of econometric model:

$$
\ln(\text{inni},t) = b_0 + b_{11}hc_{1,i,t-1} + b_{12}(hc_{1,i,t-1})^2 + b_{21}hc_{2,i,t-1} + b_{22}(hc_{2,i,t-1})^2 + b_{3}hc_{3,i,t-1} + b_{4}hc_{3,i,t-1} \times rdi_{i,t-1} + b_{5}rd_{i,t-1} + b_{6}SL(rd_{i,t-1}) + b_{7}contri_{i,t} + \mu_i + T_t + \epsilon_{i,t},
$$

where $\ln(\text{inni},t)$ is the logarithm of the innovative products output per 10,000 employees deflated by the consumer price index in region $i$ in year $t$; $contri_{i,t-1}$ is the vector of control variables, including foreign direct investments in constant prices per employee and the proportion of the regional population aged below 35 years; $\mu_i$ is the individual effect of the region $i$; $T_t$ is the time effect of year $t$; and $\epsilon_{i,t}$ is the random error.

The values of all explanatory variables of this equation are taken with a one-year lag. This approach to the specification of the model, which makes it possible to minimize the negative consequences of possible endogeneity, was used, in particular in the empirical studies of Crescenzi and Jaax (2017), as well as Ramos et al. (2012) and Cadil et al. (2014), in which the impact of human capital on the dynamics of economic development of European regions was evaluated.

Estimates of the fixed effect model are unbiased and consistent in presence of correlation between individual effects and independent variables, but they do not consider variations in data between regions, which introduces certain distortions, especially when estimating the effect of an independent variable on a dependent variable in the long run (Partridge, 2005; Tselios, 2009). The pooled model estimated by the ordinary least squares method without the inclusion of fixed effects of regions provides a better approximation of the variation of the dependent variable in space and is characterized by a smaller variance of estimates, but gives biased and inconsistent estimates in the presence of individual effects of regions and their correlation with independent variables. Thus, there is a situation of a trade-off between the biases of estimates and the quality of the approximation, which gives grounds for the presentation of estimates of each of the models. The estimates of the fixed effect model, calculated on the basis of intra-regional variation of variables over time, can be interpreted as reflecting short-term effects, and estimates of the pooled model – as reflecting long-term effects (Mairesse, 1990; Rodriguez-Pose et al., 2012).

In this study we used panel data of the Russian regions for the period after the global crisis of 2008 (from 2009 to 2018), when the growth rate of the Russian economy decreased, the share of employees with higher education increased, and the number of researchers with candidate or doctor of science degrees decreased in comparison with the previous period. These data are derived from 10 issues (2010–19) of the digest ‘Regions of Russia. Socio-economic Indicators’ published by the Russian State Statistic Service and cover 83 of the 85 Russian regions. The lack of data for the period up to 2014 forces us to exclude the Republic of Crimea and the city of Sevastopol from the analysis.

Since innovative product output does not well characterize the region’s contribution to the creation of new technologies that are competitive in the global market, we also tested our specification of knowledge production function using another dependent variable, namely the number of patent applications registered under the PCT, which was used by Crescenzi and Jaax (2017). Since data on the number of PCT patent applications by region are only available for 2009–13, the sample is limited to this period.
We estimated the following regression equation with patents for 10,000 employees as a dependent variable:

\[
pati,t = b_0 + b_{11}hc_{1,i,t-1} + b_{12}(hc_{1,i,t-1})^2 + b_{21}hc_{2,i,t-1} + b_{22}(hc_{2,i,t-1})^2 + b_{3}hc_{3,i,t-1} \\
+ b_{4}hc_{3,i,t-1} \times rd_{i,t-1} + b_{5}rd_{i,t-1} + b_{6}SL(rd_{i,t-1}) + b_{7}contri_{i,t-1} + \mu_i + T_t + \varepsilon_{i,t}. \tag{3}
\]

The relationship between educational policy tools and innovative product output has been studied using:

\[
\ln (inni,t) = b_0 + b_{1}hc_{1,i,t-1} + b_{21}hc_{2,i,t-1} + b_{22}(hc_{2,i,t-1})^2 + b_{3}hc_{3,i,t-1} \\
+ b_{4}hc_{3,i,t-1} \times rd_{i,t-1} + b_{5}rd_{i,t-1} + b_{6}SL(rd_{i,t-1}) + b_{7}contri_{i,t-1} \\
+ b_{8}NRU_{i,t-1} + b_{9}fl_{i,t-1} + b_{10}dual_{i,t-1} + b_{11}cluster_{i,t-1} + \mu_i + T_t + \varepsilon_{i,t},
\tag{4}
\]

where \(NRU_{i,t}\) is an integer variable equal to the number of national research universities in region \(i\) in year \(t\); \(fl_{i,t}\) is an indicator of the flagship university programme implementation in region \(i\) in year \(t\); \(dual_{i,t}\) is an indicator of the dual vocational education and training system implementation in region \(i\) in year \(t\) that takes the value of 1 if region \(i\) took part in the implementation of the dual model in year \(t\), and 0 otherwise; and \(cluster_{i,t}\) is an integer variable equal to the number of innovative clusters specializing in high- and medium-tech industries in region \(i\) in year \(t\).

The relationship between educational policy tools and the patent activity of Russian regions has been studied using:

\[
pati,t = b_0 + b_{1}hc_{2,i,t-1} + b_{2}(hc_{2,i,t-1})^2 + b_{3}hc_{3,i,t-1} + b_{4}hc_{3,i,t-1} \times rd_{i,t-1} + b_{5}rd_{i,t-1} \\
+ b_{6}SL(rd_{i,t-1}) + b_{7}contri_{i,t-1} + b_{8}NRU_{i,t-1} + b_{9}cluster_{i,t-1} + \mu_i + T_t + \varepsilon_{i,t}. \tag{5}
\]

Since PCT patent application data are only available from 2009 to 2013, and the effect of the flagship universities programme and implementation of the dual vocational education and training model has been realized later, we can study only the relationship between regional patent activity and such policy tools as national research universities and innovative clusters programmes.

The results of the estimation of equations (4) and (5) allow us to demonstrate correlations between policy measures and innovation activity indicators, but not the casual effects of policy measures. Issues of endogeneity are not properly addressed by the pooled model estimations. For example, national research universities could have been geared towards regions with higher patenting activity. Clusters could also have been established predominantly in regions with higher innovative product output. Even the fixed and random effects estimations may suffer from some endogeneity when regions that performed better (i.e., that showed a higher increase in innovative product output and a greater increase in more patenting) attracted better educated workers, or have been selected by politicians for the establishment of the national research universities, the flagship universities programme or the cluster programme on the basis of their better performance. Instrumental variable estimation could address this concern, but it goes beyond the scope of the paper and needs further research.

**RESULTS**

The estimation results for equation (2) are presented in Table 1.

The result of the Hausman test is in favour of the fixed-effect specification (models M1.1–M1.3), but we also present the estimation results of the random effects specification (model M1.4) and the pooled model (estimates of the ordinary least squares method excluding
individual effects of regions, model M1.5) as a robustness check. In the model’s estimated specifications, the innovative product output is positively affected by all components of human capital generated by educational programmes at different levels, and these effects are statistically significant in both the short and long runs. The effect of the share of employees with higher education on the innovative product output is characterized by the diminishing return on the expansion of higher education, which confirms the hypothesis of Balatsky (2014) about the formation of an ‘educational bubble’ in the Russian economy. The elasticity of the innovative product output on the number of researchers with candidate or doctor of science degrees increases along with an increase in R&D funding.

The estimation results for equation (3) are presented in Table 2.

Estimates of the fixed-effect model, selected by the Hausman test, show a diminishing return on the expansion of higher education. According to our estimates, the return on the increase in the proportion of employees with higher education increases before reaching 30.6% and then declines. The elasticity of patent activity by the number of researchers with candidate or doctor of science degrees increases along with an increase in R&D funding. The increase in human capital formed by vocational education and training programmes has no impact on patent activity.

We have received more optimistic estimates of the impact of human capital on patent activity in Russian regions than Crescenzi and Jaax (2017), who did not consider the variable of researchers with candidate or doctor of science degrees and their financial support. At the

|                      | M1.1       | M1.2       | M1.3       | M1.4       | M1.5       |
|----------------------|------------|------------|------------|------------|------------|
| $hc1_{i,t-1}$        | 0.047***   | 0.087 (0.067) | 0.047***   | 0.037***   | 0.005 (0.010) |
|                      | (0.016)    | (0.016)    | (0.013)    |            |            |
| $(hc1_{i,t-1})^2/100$| −0.047 (0.076) | −0.251**   | 0.266***   | 0.280***   | 0.302***   |
|                      | (0.020)    | (0.099)    | (0.096)    | (0.088)    | (0.087)    |
| $(hc2_{i,t-1})^2/100$| −0.508***  | −0.530***  | −0.559***  | −0.641***  |            |
|                      | (0.158)    | (0.154)    | (0.142)    | (0.139)    |            |
| $hc3_{i,t-1}$        | 0.136**    | 0.153***   | 0.153***   | 0.136***   | 0.145***   |
|                      | (0.058)    | (0.058)    | (0.058)    | (0.029)    | (0.020)    |
| $hc3_{i,t-1} \times rd_{i,t-1}$ | 0.051***   | 0.059***   | 0.058***   | 0.062***   | 0.078***   |
|                      | (0.015)    | (0.015)    | (0.015)    | (0.010)    | (0.008)    |
| $rd_{i,t-1}$         | 0.092 (0.194) | −0.065 (0.199) | −0.072 (0.198) | 0.160 (0.122) | 0.261*** (0.068) |
| $SL(rd_{i,t-1})$     | −0.196 (0.327) | −0.333 (0.327) | −0.339 (0.327) | −0.057 (0.162) | −0.020 (0.080) |

Control variables: Yes Yes Yes Yes Yes
Time effects: Yes Yes Yes Yes Yes
Fixed effects of regions: Yes Yes Yes No No
Random effects of regions: No No No Yes No

$R^2$: 0.376 0.430 0.416 0.510 0.527
$F$-statistics: 4.93*** 5.12*** 5.39*** 46.54***
Wald’s $\chi^2$: 234.07***

Note: Standard errors are shown in parentheses. *, **, ***Coefficient statistically significant at 10%, 5% and 1% levels, respectively.
same time, we can confirm the finding of Crescenzi and Jaax on the significant effect of the spatial spillovers of R&D expenditures on the level of patent activity in Russian regions.

Our results demonstrate that a further increase in the share of employees with higher education does not ensure the growth of innovation and patent activity in Russian regions due to the effect of diminishing returns. At the same time, the declining number of researchers with candidate or doctor of science degrees has a negative effect on the prospects for innovative development of Russian regions. The growth of employees with vocational education and training has a positive effect on innovative product output.

The estimation results for equation (4) are presented in Table 3.

According to estimates of the fixed-effect model (M3.1 specification), which is the most substantiated by the Hausman test and addresses endogeneity problem, none of the variables of educational policy tools has a statistically significant effect on the innovative product output in the short run. At the same time, estimates of the pooled model (M3.3 specification), which take the spatial variation of the data into account, indicate that the formation of national research universities, innovation clusters and the implementation of the dual vocational education and training system are accompanied by an increase in the innovative product output.

At the same time, the indicator of the formation of flagship universities does not have a significant correlation with the innovative product output in any of the estimated specifications. A possible reason is that flagship universities.

The estimation results for equation (5) are presented in Table 4.
The estimation of all the specifications under consideration demonstrates that the establishment of national research universities has positive correlation with the patent activity of the regions. Part of the positive effect of the establishment of national research universities on innovative output and patenting may stem from the attraction of new firms, especially high-tech and knowledge-intensive firms (García-Estévez & Duch-Brown, 2020). This effect needs further research in a Russian context. According to our estimations, the creation of innovative clusters did not correlate with patent activity in Russian regions.

Table 3. Results of the estimation of the relationship between educational and cluster policy tools and innovative product output in Russian regions.

|          | M3.1          | M3.2          | M3.3          |
|----------|---------------|---------------|---------------|
| \(hc1_{i,t-1}\) | 0.041*** (0.015) | 0.033*** (0.012) | 0.015* (0.009) |
| \(hc2_{i,t-1}\) | 0.241*** (0.089) | 0.260*** (0.084) | 0.475*** (0.087) |
| \((hc2_{i,t-1})^2/100\) | -0.466*** (0.144) | -0.519*** (0.137) | -0.934*** (0.142) |
| \(hc3_{i,t-1}\) | 0.127** (0.056) | 0.076*** (0.027) | 0.068*** (0.019) |
| \(hc3_{i,t-1} \times rd_{i,t-1}\) | 0.054*** (0.014) | 0.040*** (0.008) | 0.044*** (0.007) |
| \(rd_{i,t-1}\) | -0.044 (0.177) | 0.171 (0.112) | 0.197*** (0.065) |
| \(SL(rd_{i,t-1})\) | -0.356 (0.306) | -0.014 (0.150) | 0.036 (0.075) |
| \(NRU_{i,t-1}\) | 0.174 (0.109) | 0.173* (0.092) | 0.369*** (0.075) |
| \(fl_{i,t-1}\) | 0.158 (0.154) | 0.181 (0.152) | 0.182 (0.187) |
| \(dual\_{i,t-1}\) | -0.022 (0.186) | 0.139 (0.180) | 0.607*** (0.185) |
| \(cluster_{i,t-1}\) | 0.079 (0.066) | 0.114* (0.062) | 0.216*** (0.057) |

Control variables: Yes
Time effects: Yes
Fixed effects of regions: Yes
Random effects of regions: No
\(R^2\): 0.437
\(F\)-statistics: 4.68***
Wald’s \(\chi^2\): 260.54***

The estimation of all the specifications under consideration demonstrates that the establishment of national research universities has positive correlation with the patent activity of the regions. Part of the positive effect of the establishment of national research universities on innovative output and patenting may stem from the attraction of new firms, especially high-tech and knowledge-intensive firms (García-Estévez & Duch-Brown, 2020). This effect needs further research in a Russian context. According to our estimations, the creation of innovative clusters did not correlate with patent activity in Russian regions.

Table 4. Results of the estimation of the relationship between policy tools and the patent activity in Russian regions.

|          | M4.1          | M4.2          | M4.3          |
|----------|---------------|---------------|---------------|
| \(hc2_{i,t-1}\) | 0.006 (0.006) | 0.008* (0.005) | 0.006 (0.004) |
| \((hc2_{i,t-1})^2/100\) | -0.009 (0.010) | -0.012 (0.008) | -0.009 (0.007) |
| \(hc3_{i,t-1}\) | 0.019*** (0.006) | 0.006*** (0.001) | 0.007*** (0.001) |
| \(hc3_{i,t-1} \times rd_{i,t-1}\) | 0.004*** (0.001) | 0.001*** (0.000) | 0.002*** (0.000) |
| \(rd_{i,t-1}\) | 0.017 (0.014) | 0.001 (0.004) | 0.001 (0.003) |
| \(SL(rd_{i,t-1})\) | 0.044* (0.026) | 0.001 (0.004) | 0.001 (0.004) |
| \(NRU_{i,t-1}\) | 0.061*** (0.007) | 0.023*** (0.004) | 0.018*** (0.004) |
| \(cluster_{i,t-1}\) | 0.002 (0.005) | 0.001 (0.004) | 0.001 (0.004) |

Control variables: Yes
Time effects: Yes
Fixed effects of regions: Yes
Random effects of regions: No
\(R^2\): 0.496
\(F\)-statistics: 4.68***
Wald’s \(\chi^2\): 724.57***
CONCLUSIONS

The econometric analysis demonstrated that the increase in innovation activity in Russian regions’ economies is facilitated by an increase in the stocks of different types of human capital, formed by programmes of vocational education and training, higher education and doctoral programmes. At the same time, the expansion of higher education, accompanied by the reduction of high-paying jobs for researchers with candidate or doctor of science degrees, leads to negative structural changes, adversely affecting the prospects for innovative development of Russian regions. The effect of the growth of employees with higher education on innovation and patent activity is characterized by diminishing returns, and the shortage of skilled workers with vocational education and training is a fairly serious constraint to an increase in innovative product output. In addition to the negative trend towards a reduction in the number of researchers, the low level of R&D funding has a negative effect on the dynamics of innovation and patent activity, reducing the impact of the educational capital concentrated in the R&D sector.

The results of this study demonstrate the need to improve educational programmes and increase funding, especially at the levels of doctoral programmes and vocational education and training. Improving the quality of training of researchers able to participate in the innovative development of regions requires the implementation of collaborative doctoral programmes in the Russian context, similar to those successfully implemented by universities together with industrial partners in Denmark, Sweden, France and some other European countries. The level of scholarship provision, which is currently minimal and does not allow Russian doctoral students to concentrate on research work, should be increased. Improving the Russian vocational education and training system requires scaling the experience of regions participating in the pilot project of the Agency for Strategic Initiatives, which aims to implement the German model of dual vocational education and training. This requires the development and implementation of a special programme of public support for regional chambers of commerce and industry capable of mediating between employers and vocational education and training institutions.

We have not been able to identify the statistically significant relationships between the educational policy tools used after the 2008 crisis and the growth of innovation and patent activity in Russian regions using a fixed-effect model. At the same time, estimations using specifications that consider spatial variation of the data showed that the presence of a national research university in a region and its participation in the programme of implementation of the dual model of vocational education and training has a positive correlation with the growth of innovative product output in the long run. The establishment of a national research university in a region has a positive correlation with the growth in the number of applications for international patents even within the fixed-effect model.

However, these estimates may be biased because of endogeneity problem. Instrumental variable estimation could address this concern, and it is an interesting task for further research.

NOTE

1 In Russia, contrary to most countries around the world, there are two scientific degrees: candidate of science and doctor of science, each of which is awarded based on the results of thesis defence. The requirements for applicants for the candidate of science degree are quite similar to those for a PhD in the European Union. The doctor of science thesis solves more ambitious scientific problems, is larger in volume and its results must be published in at least 15 journal articles. Doctor of science theses are usually defended by more mature scientists applying for the position of full professor. Differences in the academic qualifications and reputations of candidates of science and doctors of science teaching at universities are in many respects similar to
differences in the academic qualifications and reputations of doctors working as assistant or associate professors and full professors in the European Union.

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ORCID

Valentina Teslenko http://orcid.org/0000-0003-1574-9359
Roman Melnikov http://orcid.org/0000-0001-6335-2458
Damien Bazin http://orcid.org/0000-0002-0020-5044

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