Empirical Economics (2022) 62:2619–2643
https://doi.org/10.1007/s00181-021-02095-3

Effects of R&D spending on productivity of the Russian firms: does technological intensity matter?

Oleg Mariev[1,2] · Karina Nagieva[1] · Andrey Pushkarev[1] · Natalia Davidson[1] · Kazi Sohag[1]

Received: 26 October 2020 / Accepted: 29 June 2021 / Published online: 10 July 2021
© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2021

Abstract
We investigate the impact of R&D spending on firm productivity through innovation and human capital channels. To this end, we apply the structural CDM model to analyse a comprehensive Russian-firm level data obtained from the Business Environment and Enterprise Performance Survey supplemented with the Regional Integral Index of Innovation Development. We consider internal and external human capital as well as different levels of firms' technological intensity. Our first stage of analysis demonstrates that dissatisfaction with employees' specialisation, import of intermediate products, and firm's association with larger enterprise augment total R&D expenditures. The second stage of analysis reveals that R&D expenditures, cooperation with universities, personnel training, and regional innovations spur the firm's innovative sales. Finally, the last stage of our analysis affirms our proposition that innovative sales, capital and labour costs per employee accelerate productivity. Our estimation is robust considering the regional differences. Our empirical findings provide several policy implications.

✉ Andrey Pushkarev
a.a.pushkarev@urfu.ru

Oleg Mariev
o.s.mariev@urfu.ru

Karina Nagieva
nagieva1995@list.ru

Natalia Davidson
natalya.davidson@gmail.com

Kazi Sohag
ksokhag@urfu.ru

1 Graduate School of Economics and Management, Ural Federal University, Mira 19, Yekaterinburg, Russia

2 Institute of Economics of the Ural Branch of the RAS, Yekaterinburg, Russia

Keywords R&D · Innovations · CDM model · Firms · Industries · Human capital · Technological intensity

1 Introduction

Innovation is crucial for a firm's productivity and long-term national socio-economic growth and development (OECD OECD; Ortega-Argiles et al. 2011). However, while promoting innovation, a firm requires strategy, investment, and relationships (Conte and Vivarelli 2014). Moreover, innovation is vital for a transitional economy like Russia, where business environment and regional development vary considerably across regions. Besides, firms in Russia lag behind with innovative activities and consequently experience relatively low labour productivity. Nevertheless, in recent years, Russian firms strive to foster innovative activities importance in line with the country's national development plan. Given this background, we aim to assess the impact of research and development (R&D) spending on labour productivity through the channel of innovations. In addition, we address personnel training, organisational cooperation, and regional technological advancement for the case of Russian firms.

Several propositions motivate us to scrutinise the R&D and labour productivity nexus. First, given the institutional challenges of the transitional economy of Russia, it is helpful to understand how a firm can improve its competitiveness (Ramadani et al. 2019). In this connection, we argue that innovation is the critical driver for economic diversification and private sector development in Russia, enabling the country to reduce its dependence on natural resources. When promoting innovation, several studies document that R&D spending and human capital are essential (e.g. Roud 2007; Gallié and Legros 2012; Zemtsov et al. 2016; Brunow et al. 2018; Fonseca et al. 2019). However, prior studies overlook the partial impact of external human capital (formal schooling), and the employee training carried out by firms. We fill this loophole and shed light on the importance of skills development to improve innovative outcome. Besides, a prior study recommends contextualising the firms' sizes and sectoral differences to explain the firms' innovation (Hewitt-Dundas et al. 2019). Therefore, we measure the role of human capital to improve innovations considering high-tech and low-tech (including medium-tech) firms in our set-up.

Second, prior studies argue that firm innovations are accelerated by not only its R&D activities but also innovation spillovers over the industry, national and international level (Griliches 1979; Pakes and Griliches 1984; Crepon et al. 1998; Hall 2011; Morris 2018). Evidence shows that cooperation (Hewitt-Dundas et al. 2019; Haus-Reve et al. 2019; Roper et al. 2017) and a region's technological capital (Lopez-Rodriguez and Martinez-Lopez 2017) spur innovation. Cooperation implies an active position of a firm that can develop relations with various stakeholders, including customers, suppliers, and others, and make these interactions beneficial for its innovative activity. At the same time, a single firm is less likely to influence the innovative regional environment, at least in the short run. In addition, company characteristics play a critical role in the innovation process (Bartoloni and Baussola 2018).

To summarise, we contribute to the literature in two ways. First, we extend the existing research on the firms' innovations and productivity in the transitional economy of

Russia (Zemtsov et al. 2016; Roud 2007) by considering manufacturing firms with different technological intensities. Among other findings, we reveal the importance of R&D for high-tech firms and a substantial contribution of innovation to productivity for all firms. Second, we shed light on the knowledge spillovers arising from cooperation established by a firm versus the knowledge spillovers from the regional innovation climate that affect a firm. Our empirical findings reinforce the importance of a firm's cooperation with other organisations at the regional and national level for achieving higher innovation and productivity. To assess the impact of R&D spending on productivity, we adopt the Crepon–Duguet–Mairesse (CDM) model (Crepon et al. 1998), which tracks the link between R&D, innovation and productivity. It also allows to consider several control variables associated with productivity.

As for the firm-level characteristics, some empirical papers focusing on developing countries and transitional economies demonstrate that large firms are more likely to innovate. Still, smaller firms' share of innovative sales tends to be higher (Fagerberg et al. 2010). Therefore, we account for firm-level characteristics in our set-up. Besides, we consider the overall regional innovation climate, the firm-level human capital and cooperation, and the firm characteristics such as size and age in our empirical model.

The rest of the paper is organised as follows. The next section provides a brief review of research focused on our topic, followed by a description of the data and methodology used. The following sections present and discuss the results of the econometric analysis, while the last section concludes the paper and suggests policy implications.

2 Background and the existing research

2.1 The link between firms' R&D, innovation and productivity

The role of R&D in firms' productivity attracts interest as it is associated with the importance of factors other than the growth of labour and capital, the most apparent determinants of productivity growth (Hall 2011). The interconnection between R&D, innovation, and productivity has been well discussed since recently, and sources of innovations both internal and external to firms have been amply addressed in the literature (Griliches 1979; Pakes and Griliches 1984; Lööf et al. 2001; Hall 2011; Morris 2018; Ramadani et al. 2019). Another group of models that provide a background for analysis of the connection between R&D, innovation and productivity are R&D growth models that extended standard (Solow 1957) model to implement endogenous technological change.

Fagerberg et al. (2010) and Martin (2012) provided a comprehensive review of research on innovation. Capabilities for innovation at the national and firm levels vary (Fagerberg et al. 2010), while innovations and innovation climate positively affect productivity (Solow 1957; Chudnovsky et al. 2006; Griffith et al. 2006; Masso and Vahter 2008; Raymond et al. 2015).

To analyse the impact of R&D and innovation on productivity, the knowledge production function was introduced and later developed in the CDM model. While earlier studies relied on the augmented (knowledge) production function with R&D proposed by Griliches (1979), many recent studies employed the CDM framework (Lööf et al.

2017), initially devised by Crepon et al. (1998). Based on the objective of this study, we adopt the CDM model to analyse the effects of innovations on productivity, taking the endogenous nature of this connection into account. CDM model consists of three stages linking R&D, innovations, and productivity at the firm level. The first stage of the model explores the driving factors that spur the R&D process. The second stage sheds light on the impact of R&D expenditures on innovations. The third stage reveals the impact of innovations on productivity. Crepon et al. (1998) found a positive effect of R&D activities and innovations on value-added per employee among French manufacturing firms. Studies employing the CDM model and its modifications demonstrate positive effects of R&D spending and innovations on productivity, at least in the long run (Marotta et al. 2007; Cirera 2015; Raymond et al. 2015; Lööf et al. 2017; Teplykh 2018).

There is a shortage of studies on transitional countries in this regard, although the innovation process in such economies is of particular interest. Firms in transitional countries require substantial innovation to compete in the global markets. At the same time, empirical research shows that transitional countries are characterised by rent-seeking behaviour and might lack some of the critical components needed for the innovation process, such as traditions of entrepreneurship and access to finance (Ramadani et al. 2019). Prokop et al. (2017) used Community Innovation Survey data for the Czech Republic, Slovakia, and Hungary, and multiple linear regression models to find that proper targeting of innovation drivers significantly contributes to innovative turnover growth and may increase firm and national competitiveness. They emphasised that economic policy should be aimed at promoting knowledge spillovers.

There is even less research on innovations for former Soviet Union countries than for Central and Eastern European countries (Vakhitova and Pavlenko 2010; Krusinskas et al. 2015). Vakhitova and Pavlenko (2010) used the CDM model and 2004–2006 data on Ukrainian firms to find that firms which introduced innovation once are more likely to perform R&D and innovate again, while past productivity affects current innovations.

Zemtsov et al. (2016), based on the model of knowledge production functions and regional data for Russia covering the period 1998–2011, found that the quality of human capital has the most significant impact on the number of patents; other influential factors include buying equipment and spending on basic research, while the 'centerperiphery' structure characterises regional-level innovation activity. Roud (2007), employing Rosstat data collected in 2005 for 26,000 Russian firms and the CDM model, found a positive impact of innovation on productivity for the high-tech manufacturing sector and identified obstacles to innovation, including lack of financial resources and unfair competition caused by non-uniform state support. Besides, firms in Russia are focused on buying technologies rather than on developing them and are limited by the lack of human capital. We extend the analysis to high-, low-, and medium-tech firms, thereby covering a broader segment of firms in Russia's manufacturing sector and applying the CDM model. Thus, we fill the gap in the literature by studying the determinants of R&D, innovations, and productivity for the transitional economy of Russia.

2.2 Human capital in innovation process: firms with different technological intensities

The discussion of innovation and productivity in the literature involves human capital along with R&D and external sources of innovation (Roud 2007; Ayyagari et al. 2012; Zemtsov et al. 2016). Gallié and Legros (2012) report positive impacts of R&D intensity and employee in-service training on the number of patents, and emphasise the importance of human capital for innovation for the French industrial firms over the period 1986–1992. Research based on Business Environment and Enterprise Performance Survey (BEEPS) data for Spanish manufacturing and service sector firms demonstrate positive impacts of radical innovation and personnel training on labour productivity (Guisado-Gonzalez et al. 2016).

Based on data from over 6000 Portuguese firms, Fonseca et al. (2019) find that the share of workers with a college education in the workforce is vital for firms' innovation and performance, but Haus-Reve et al. (2019) reached the opposite conclusion—that the share of educated employees is not significant for the share of turnover from new or significantly improved products. Such contradictory findings imply that an appropriate balance between abstract and non-abstract tasks is required in the stage of implementing innovations. Brunow et al. (2018) used a probit model to analyse firm-level observations for 2008–2015 in Germany, finding that firms employing creative and science, technology, engineering and mathematics (STEM) workers are more innovative than other firms. Moreover, the employment of STEM workers is found to create positive spillovers in German cities.

These findings emphasise the importance of the quality of human capital available to firms and personnel training aimed at developing a variety of skills needed for successful innovative processes. Moreover, a recent study by the World Bank emphasises that all stages of education, starting from an early age and the health of the individuals, are important for human capital formation (World Bank 2019). Our study employs two measures of human capital along with R&D: inadequacy of worker specialisation and personnel training. The first indicator reflects external human capital, i.e. the qualifications of workers available to the firm. The second one demonstrates firms' efforts in improving their human capital. While both indicators are studied in the literature, we contribute by comparing their relative importance.

The key channels of interaction between R&D, innovation, and productivity tend to differ in their statistical significance and magnitude across industries with different levels of technological development (Baum et al. 2017). Researchers find a significant positive effect of knowledge stock on enterprise productivity, emphasising that firms in high-tech sectors experience the most significant impact of R&D on productivity (Ortega-Argiles et al. 2011). We account for the firms' heterogeneity in technology and knowledge by estimating the model for subsamples of firms belonging to low-, medium-, and high-tech industries. Given this backdrop, we put forth the following hypothesis:

Hypothesis 1 Human capital affects the innovation activity of firms with different technological intensity differently.

2.3 Innovative environment and cooperation in innovation process

This section addresses external sources of innovations. The knowledge production function distinguishes between the impacts of firms' R&D and R&D spillovers on firm productivity (Griliches 1979; Pakes and Griliches 1984; Hall 2011). Hall (2011) summarises the approaches to modelling the impact of innovation on productivity using knowledge production function, an augmented Cobb–Douglas function, considering both firm-level R&D and other firms' R&D, i.e. externalities. R&D and non-R&D innovation activity are beneficial for productivity (Lopez-Rodriguez and Martinez-Lopez 2017). Along with the firm's own ideas and internal R&D, cooperation with various organisations is found to be necessary for innovation, as valuable ideas can come from external sources (Fagerberg et al. 2010). Technology acquisition combined with R&D can contribute substantially to product innovation, but the relative importance of this effect can differ for firms of different sizes and working in different technological domains (Conte and Vivarelli 2014).

Firms acquire the knowledge needed for innovation based on technological diffusion mechanisms, which matters for firms' performance (Orlando 2004; Aldieri et al. 2018; Ramadani et al. 2019). While most studies show that R&D leads to innovation, it is not only firms investing in and conducting R&D who innovate. Along with R&D, external knowledge derived in various ways, including networks and cooperation, leads to innovation. Ferraris et al. (2017) find that openness for external and internal knowledge is beneficial for subsidiaries' innovation performance. Based on UK surveys, Roper et al. (2017) report that only interactive collaboration generates positive externalities, while non-interactive contacts bring negative external effects, making it important to facilitate cooperation and counter illegal copying or counterfeiting.

Aldieri et al. (2018), based on an augmented Cobb–Douglas production function proposed by Griliches (1979), concludes that firms with the same level of absorptive capacity, working in economic areas closer to the world technology frontier, benefit more from knowledge spillovers than from rent spillovers. Inter-industry externalities (described by Jane Jacobs) were found to matter much more than Marshallian, intra-industry externalities. Orlando (2004) uses a knowledge production function (Pakes and Griliches 1984), and finds the existence of industry-specific spillovers. Haus-Reve et al. (2019) study innovations of firms in Norway in 2006–2010 and find positive impacts of scientific and supply-chain collaboration on firm-level innovation. Knowledge accumulation enhances firms' ability to absorb new ideas and innovate (Cohen and Levinthal 1990). Cooperation with universities and research centres is also beneficial for firms' innovation (Triguero et al. 2013; Caloghirou et al. 2021; Hewitt-Dundas et al. 2019).

Lopez-Rodriguez and Martinez-Lopez (2017) consider R&D and non-R&D innovation activities (acquisition of new technology; the purchase of advanced machinery, design and production engineering etc.) within an augmented macroeconomic growth model and estimate the impact of these activities on the TFP for 26 EU countries for 2004-2008. They find the impact of R&D on TFP growth to be twice as significant as non-R&D activities. Besides, they find evidence of knowledge transfers in favour of technologically less advanced economies. Morris (2018) uses cross-country panel data, employs the CDM model and takes firms' heterogeneity into account to find firms' R&D and external sources of knowledge (such as information spillovers associated with FDI, import, export, and foreign technology) to be significant for some subsamples and estimation techniques. The finding suggests potential benefits from cooperation with foreign stakeholders; therefore, we consider the variables 'cooperation with foreign consumers', 'cooperation with foreign suppliers' and 'import', which brings us to the following hypothesis. Indeed, while a firm cannot directly influence the innovative regional environment, it can cooperate with various stakeholders, enhancing its innovation.

Hypothesis 2 Both cooperation with various organisations and regional innovative environment are important for firms' innovation activity.

To test these hypotheses, developed to fill the gap in the current research on innovation, we employ BEEPS data and the CDM model, as discussed in the following section.

3 Data and methods

The CDM model (Crepon et al. 1998) allows us to reveal motivation for R&D expenditures, their impact on actual innovations, and the effect of innovations on productivity, shedding light on the mechanism behind innovative activities and their outcomes. The CDM model is a structural model enabling tracking the innovation process and dealing with endogeneity (Crepon et al. 1998; Lööf et al. 2017). The mechanism of the CDM model contains three stages. Based on the existing research analysed above (Bozic and Botric 2011; Hall et al. 2013; Cirera 2015), the variables for each stage were chosen to reflect the factors behind R&D activities, actual innovations, and enterprise productivity. The first stage reflects a firm's decision if to invest in R&D and how much to invest. Along with the Regional Integral Index of Innovation Development (RIIID), we include (1) external factors behind R&D activities—competition, subsidies, business environment conditions—obstacles related to business licensing (permission to carry out a certain type of activity) and permits, tax rates, inadequacy of worker specialisation; and (2) individual characteristics of firms—age, size, being a part of a larger enterprise, being an importer. In BEEPS[1] all firms are asked whether and how much they invest in R&D. As can be expected, some firms report zero expenditures. However, zero outcomes should also be taken into consideration to avoid a selection bias. Besides, the process describing R&D investment and innovative results is the same for all firms (Griffith et al. 2006). To account for firms with zero investments, we apply a Poisson estimator, following Cirera (2015). The equation in the first stage is as follows:

$$\log E(rd_{i,j}) = \beta_0 + \beta_1 * x_{i,j}, \tag{1}$$

[1] We utilise cross-sectional data for 2012–2014 obtained from Business Environment and Enterprise Survey (BEEPS). Note that BEEPS collaborated with World Bank Enterprise Survey (WBES), which conducted in 2008, 2012–2014, and 2019. However, we were unable to merge our dataset with the dataset for 2019 obtained by World Bank Enterprise Survey (WBES) to convert into panel format due to only 38% overlapping.

where *rd* is R&D expenditures of the *i*th firm belonging to the *j*th group of industries, i.e. low and medium-tech or high-tech industries, *x* accounts for internal and external factors. In this case the observed values *rd* Poisson.

A simple linear model without log $E(rd_{i,j})$ cannot be used because *rd* can take on only positive values. A log transformation $E(rd_{i,j})$ of solves this problem and takes on values from $-\infty$ to ∞ . Moreover, the Poisson regression does not contain separate error term like in linear regression, as $\lambda = E(rd_{i,j}) = \mathrm{Var}(rd_{i,j})$ determines both the mean and the variance of a Poisson random variable (Roback and Legler 2021). At this stage, quality of human capital at the regional level, i.e. human capital available to the firm is included.

The second stage describes the impact of R&D expenditures on the innovative result. To represent actual innovative result, we use innovative sales reported by firms. It is one of the common approaches in literature (Conte and Vivarelli 2014). An alternative indicator of innovations is the number of patents. However, several limitations are associated with this type of indicator. First, not every invention is patented instantly, especially if it is for internal use only (like a specific way of tracking stock levels of a specific warehouse). Besides, patent data does not show whether an invention of a new product, service or process was successfully commercialised (Carlino and Kerr 2014; Gallié and Legros 2012).

The predicted R&D expenditures received in the previous stage are used, and the OLS method is applied to estimate this equation. This stage of the CDM model tracks the link between innovative inputs and outputs, reflecting the firm's innovative efficiency. As the innovative efficiency is assumed to depend upon human capital at the firm level, the variable 'training of personnel' is included in the equation. As discussed in the previous section, there is evidence that along with firm's R&D, external innovation sources are important for the firms along with the firm's R&D. Therefore, we introduce dummy variables reflecting licensing of technology, cooperation with domestic suppliers, foreign suppliers, domestic consumers, foreign consumers, and with universities. This allows us to distinguish between companies that cooperate and those that perform innovations based only on their capabilities. The general form of the second stage equation is the following:

$$\log InnovativeSales_{ij} = \beta_0 + \beta_1 * Z_{i,j} + \epsilon_{i,j}, \tag{2}$$

where Z is predictors of innovative sales, including predicted R&D expenditures, sources of cooperation, and personnel training.

At stage three, we estimate the impact of the innovative sales per employee predicted at the second stage, on the firm's productivity. Apart from this indicator and the regional Integral index of innovation development, the explanatory variables are the production factors: cost of capital per employee and labour costs per employee. The variables at this stage are chosen based on the Cobb–Douglas production function that contains production factors and total factor productivity. Thus, the production factors included in the model are capital and labour. At the same time, innovative sales per employee reflect shifts in the production function associated with the firm's innovations, and externalities, i.e. regional level innovations, are also considered (Solow 1957). Thus, for the third stage of modelling, a modified Cobb–Douglas production function is used:

$$\log y_{i,j} = \delta_0 + (1 - \alpha - \beta) * \log h_{i,j} + \alpha * \log k_{i,j} + \beta * \log l_{i,j} + \epsilon_{i,j}, \quad (3)$$

where y, h, k, l—is revenue, innovative sales, capital and labor costs per employee (to account for the firms' size). Although using revenue as the output indicator has some limitations, it was the best available choice

At each stage, we included the RIIID of the Russian regions for 2012, reflecting the innovative and socio-economic conditions of the region (Gokhberg 2014), with industrial dummies reflecting specific features of various industries.

To estimate all stages of the CDM model, we used a sequential 2SLS procedure by adding the predicted dependent variables from the previous step to the following equation, thus mitigating the endogeneity issues (Lööf et al. 2017).

We employ data from the BEEPS on Russian companies for 2012–2014. BEEPS Survey involves around 4220 enterprises from all federal districts of the Russian Federation (more precisely, 64 state enterprises and 4167 private firms, including 146 private enterprises with foreign capital). It is worth noting that the BEEPS data is representative and covers all of Russia.

Unfortunately, it is impossible to add more periods to the data, as the overlay between different waves of the BEEPS is somewhat limited in terms of both surveyed firms and the questions they were asked. Originally the CDM model was applied to study cross-sectional data. The authors of the model recognise this as a drawback, but estimate the cross-sectional data due to the absence of panel data. Moreover, they point out that, compared to time-series data, it is unclear which type of data provides more reliable estimates. Still, cross-sectional data is expected to give plausible results (Crepon et al. 1998, p. 136).

Since the survey involves firms from different industries with various features and attitudes towards innovations, the model is estimated for three samples: general (all firms); group 1—low- and medium-technology firms ($N = 922$); and group 2—high-tech firms ($N = 642$). The split sample allows us to compare the deviations of groups 1 and 2 from the average results (all firms). Classification of industries is based on the OECD methodology (Hatzichronoglou 1997), which relies on differences in the intensity of firms' R&D expenditures. The remaining companies belong to services and trade, having a particular attitude towards innovations; this paper does not consider this group of firms (Table 1).

Our data covers all federal districts of Russia. We present the distribution of firms in Table 2. As one can see, the largest federal district in terms of companies is the Central federal district, where Moscow is located. The second-largest district is Volga federal district, flowed by Siberian and North-Western federal districts. This distribution generally corresponds to the information reported by the Russian Federal State Statistics Service (RFSSS).

We suggest that OECD classification can be used for this research, as there is no similar classification based on the direct R&D intensity officially adopted for Russian companies. On top of that, the OECD applies this classification to both developed countries and transitional economies. Besides, this approach was also adopted by Eurostat for its NACE Rev. 2 classification. Since the Russian OKVED 2 industrial

Table 1 Distribution of firms by technology groups

	Group name	Industry
Group 1	Low-tech industries	Food industry
		Tobacco products
		Textile
		Clothing
		Tanning and leather
		Wood (forest industry)
		Paper and paper products
		Publish and print
		Furniture
	Medium-tech industries	Coke and petroleum products
		Plastics and rubber
		Non-metallic mineral products
		Base metals
		Finished metal products
Group 2	High-tech industries	Chemical products (pharmaceuticals, etc.)
		Cars and equipment
		Office equipment
		Electronics
		Communication equipment
		Precision tools
		Motor vehicles
		Other transport equipment
		IT industry

Table 2 Distribution of firms by federal district

Federal district	BEEPS		RFSSS
	Quantity	Share, %	Share, %
Central	1124	26.64	38.55
North-Western	484	11.47	12.61
Volga	922	21.85	15.98
South	328	7.77	6.52
Urals	199	4.72	8.12
North-Caucasus	120	2.84	2.81
Siberian	709	16.80	11.02
Far Eastern	334	7.91	3.99

classification is the same as NACE Rev. 2, we assume that Hatzichronoglou (1997) approach can be applied to Russian firms.

All qualitative indicators are taken from BEEPS and are transformed into dummy variables, following the procedure presented by Bozic and Botric (2011). In particular,

Table 3 Descriptive statistics of innovative sales by size and groups of firms

Groups of firms	Size of firms	Innovative sales (mln rub)	
		Mean	Maximum
Total	Large	76.7	9750
	Small and medium	4.86	3600
Group 1	Large	115	9750
	Small and medium	7.1	2400
Group 2	Large	155	4500
	Small and medium	7.1	1500

Table 4 Descriptive statistics of the share of innovative sales in revenue by size and groups of firms

Groups of firms	Size of firms	Innovative sales in revenue, %	
		Mean	*Maximum*
Total	Large	22.77	100
	Small and medium	32.81	100
Group 1	Large	18.23	70
	Small and medium	31.34	100
Group 2	Large	26.46	100
	Small and medium	34.33	100

if a firm has stated that a specific barrier is a main or significant issue, the corresponding variable is marked as 1, and it is marked as 0 otherwise. This approach allows us to use these variables in the standard modelling procedure.

Table 3 shows the descriptive statistics of innovative sales. The analysis is aimed at two industrial groups (the first one is low- and medium-tech; the second one is high-tech); and two size groups (the first group is small and medium companies; the second group is large companies). The table shows that large companies lead in all samples in terms of average and maximum values of innovative sales, with the highest average value being noted in high-tech industries (Group 2). However, sales resulting from innovations are recorded for low- and medium-tech firms (Group 1).

However, if innovative sales are considered a revenue share, the finding is changed (see Table 4).

The largest share of innovations belongs to small and medium-sized firms, while the high-tech industry is still the leading sector. In other words, small firms are more inclined to introduce innovations. However, large companies enjoy more significant sales due to their production scale, better opportunities, and expanded markets, even if their share of innovations is smaller. In the literature, there is evidence that large high-tech companies have a higher tendency to perform their R&D, mainly product-oriented. In contrast, smaller low-tech companies tend to carry out technological acquisition and aim at process innovations (Conte and Vivarelli 2014). Overall, these statistics are slightly lower than the proportion of innovative sales to total sales for the firms in developed countries, for example, in Norway (36%), Finland (34%), and Sweden (33%) (Lööf and Heshmati 2003). The results of estimating the CDM model are presented in the next section. The results of estimating the CDM model are presented in the next section.

4 Results and discussion

4.1 Main results

Table 5 shows the results of the first stage of the CDM model, with firms' R&D expenditures as a dependent variable. Results of the first stage of the CDM modelling conform to our expectations. Overall, the high significance of all indicators in all groups is observed. At the same time, there are also some differences among industrial groups and deviations from the average results. As can be observed from Table 5, in a general sample and in the group of high-tech industries, large firms are more likely to invest in research and development. This result could be expected, since, in high-tech industries, business success depends on the development of new products. Therefore, high-tech firms need to spend a lot on R&D, and it is usually larger firms that can afford this, as they have more opportunities and resources.

Moreover, many large firms operate at the international level and need innovations to stay competitive. According to the Schumpeterian hypothesis, large firms enjoy better access to external and internal finance. Besides, large firms are more diversified, and therefore less affected by uncertainty. Large firms enjoy the scale and scope economies from R&D projects. Our hypothesis is supported by empirical evidence (Symeonidis 1996; Gallié and Legros 2012). At the same time, the results in the literature are controversial, such as the firm's size affecting the likelihood of innovating, while negatively affecting product innovations (Conte and Vivarelli 2014).

Our decomposed analysis shows that younger firms invest more in R&D relatively to older firms in the overall sample and Group 1 (low- and medium-tech firms). The finding is sensible since new firms need to be as competitive as possible to settle on the market. Older firms already have their market share and are likely to innovate if they see an opportunity to increase it. Besides, some older firms may be in decline, lacking resources for R&D.

Competition, i.e. the number of competitors, proved to be significant and negatively affected investment in R&D for the overall sample and for the firms belonging to high-tech sectors, while for low- and medium-tech industries, it proved insignificant. There is evidence of the positive effect of competition on R&D (Gallié and Legros (2012)). However, the results might depend on the business climate and other countries' characteristics. Moreover, if the competition pressure is too high, enterprises may lose profit as the number of players on the market increases as their funding sources commensurately decrease (Avdasheva et al. 2006). In addition, high-tech firms are fragile in Russia. Due to the obstacles that they face, they cannot successfully compete even on the domestic market. As for low- and medium-tech firms, they are inert in terms of R&D and will instead acquire existing technologies. All this may also indicate low demand for innovations on the Russian market. The share of innovative firms is

Table 5 CDM modelling for the Russian firms: first stage

The sum of R&D expenditures	Total sample	Group 1	Group 2
Size	1.860***	0.604	2.382***
	(0.349)	(0.563)	(0 .392)
Age	−0.018**	−0.081***	−0.007
	(0.008)	(0.031)	(0.008)
Competition	−0.008*	−0.003	−0.011*
	(0.004)	(0.006)	(0.006)
Part of the larger enterprise	1.031***	0.767	0.846**
	(0.301)	(0.666)	(0.408)
Subsidies	0.093	0.813	0.017
	(0.453)	(0.713)	(0.555)
Taxes	0.007	−0.075	0.068
	(0.396)	(0.639)	(0.458)
Inadequacy of the workers' specialisation	0.997***	1.098*	0.829**
	(0.332)	(0.618)	(0.361)
Import	1.3148***	1.610***	1.228***
	(0.398)	(0.567)	(0.434)
Business licensing and permits	0.515	0.394	0.652*
	(0.317)	(0.546)	(0.365)
Index of innovation development	3.156	−3.475	5.757*
	(2.515)	(3.501)	(2.935)
Industrial dummies	Yes	Yes	Yes
Wald test	17675.39***	5755.20***	4248.73***
Pseudo R^2	0.489	0.292	0.630

***Significant at the 1% level, **At the 5% level, *At the 10% level. The standard errors in parentheses. Group 1 contains low- and medium-technology firms ($N = 922$); and group 2 contains high-tech firms ($N = 642$)

among the lowest compared to the other countries (Indicators of Innovation Activity 2018).

In the general sample and the group of high-tech industries, firms comprising large enterprises spend more on R&D. As explained above, larger firms have more resources that can be employed in R&D processes compared to smaller firms operating on their own. In addition, firms belonging to a large enterprise have access to knowledge and skills within this enterprise, representing wider expertise and higher innovative capacity, making the R&D process more effective.

Receiving a subsidy turned out to be insignificant for investing in research and development in all three groups. On the one hand, this may suggest that subsidies received from any sources could be directed to other purposes. For example, for some firms, particularly for the large ones, subsidies might be an outcome of good relations with the authorities. In such a situation, the availability of subsidies for a firm would not necessarily be associated with the firm's innovative activity. On the other

Table 6 CDM modelling for the Russian firms: second stage

The logarithm of innovative sales	Total sample	Group 1	Group 2
Predicted sum of R&D expenditures	3.42e−07***	8.85e−07	2.38e−07***
	(1.04e-07)	(8.62e−07)	(7.82e−08)
Licensing	5.312***	1.515	9.071***
	(1.898)	(2.515)	(2.273)
Domestic suppliers	8.037***	9.708***	6.482***
	(1.090)	(1.389)	(1.616)
Foreign suppliers	6.301***	6.531**	5.857***
	(1.761)	(2.726)	(2.158)
Domestic consumers	10.433***	13.559***	8.401***
	(1.037)	(0.669)	(1.490)
Foreign consumers	11.035***	15.428***	8.215*
	(3.192)	(0.659)	(4.380)
Cooperation with universities	6.155***	7.650**	4.659**
	(1.873)	(3.207)	(2.222)
Training of personnel	1.126***	0.477	1.911***
	(0.346)	(0.433)	(0.573)
Index of innovation development	11.180***	8.873***	16.007***
	(2.362)	(3.012)	(3.793)
Industrial dummies	Yes	Yes	Yes
Adjusted R^2	0.181	0.167	0.203

***Significant at the 1% level, **At the 5% level, *At the 10% level. The standard errors in parentheses. Group 1 contains low- and medium-technology firms ($N = 922$); and group 2 contains high-tech firms ($N = 642$)

hand, enterprises often have little knowledge of state support programs, and not every enterprise knows how to use these opportunities.

Barriers to business activity, except tax rates, were significant for almost all industry groups; a positive coefficient indicated that innovative firms inevitably face some obstacles and consequently experience an increased burden. Import as an indicator of international economic activities is positive and significant for R&D in all groups. A high level of innovative regional development positively impacts the propensity to innovate for high-tech firms, which can be explained by their relatively greater sensitivity to an innovative climate.

Table 6 presents the results of the second stage of the CDM modelling. Table 6 reports that the return on investment in R&D is more profound for the general sample and high-tech firms, implying a more substantial impact of R&D for firms with greater technological intensity. Our result is relatively consistent with reality, as high-tech industries, unlike low- and medium-tech industries, are the most innovative ones. Their share of development costs in value-added is the highest. Moreover, the productivity of low and medium-tech firms depends relatively more on physical capital. There are similar findings in the literature (Ortega-Argiles et al. 2011).

Besides, there is evidence that firms tend to be involved in non-R&D activities such as minor modifications or incremental changes to products and processes, imitations or the adoption of innovations, and the combination of existing knowledge in new ways. For example, the European Community Innovation Survey showed that almost half of innovative firms in 15 European countries performed non-R&D activities (Lopez-Rodriguez and Martinez-Lopez 2017). Guisado-Gonzalez et al. (2016) also pointed out the role of non-R&D activities, such as acquiring knowledge embodied in new machinery and equipment, emphasising that this role can be positive or negative, depending on the efficiency of the purchased equipment, among other factors.

The second step involves dummy variables reflecting various sources of knowledge, i.e. the ways how innovations were introduced. The results show that almost all sources are positive and significant for an innovative result in all groups of firms, including firms of low- and medium-tech industries. It suggests that it is important for the low-tech firms to cooperate with various organisations in the development of innovations, as they might have fewer resources for performing their investments in R&D. This result is in line with the literature (Conte and Vivarelli 2014).

All these sources increase the innovative potential of enterprises. Licensing and cooperation with stakeholders, including universities, is of great importance for the successful commercialisation of newly developed products or services. The exception was licensing for group 2: for firms from low- and medium-tech industries, this form of cooperation was the least popular or not used.

Personnel training proved to be positive and significant for the general sample and high-tech firms, indicating the importance of unique skills and knowledge of personnel for innovations. The finding implies that high-tech firms need to train their personnel because success in innovations is crucial for them. Meanwhile, the firms of low- and medium-tech industries do not have the opportunities or have not had a need yet to train personnel with special skills for innovations.

The last column of Table 7 shows that productivity improvement from innovative sales is more profound for high-tech firms than low and medium-tech firms. In other words, firms' investments in R&D lead to successful commercialisation. These results are comparable to the evidence in the literature showing that high-tech sectors benefit relatively more from R&D investments, although there might be another point of view: that low and medium-tech firms would catch up on R&D, and therefore gain more in terms of productivity (Ortega-Argiles et al. 2011). In other words, although for low- and medium-tech industries, innovations tend not to be a priority area, innovative sales positively affect enterprise productivity.

As for the traditional production factors, as expected, an increase in capital per employee led to increased labour productivity (in the total sample and in group 1). Insignificance for high-tech industries may indicate that the existing machines and equipment are outdated and do not contribute to productivity. Labour costs per employee also positively affect firms' productivity, and their contribution to the dependent variable is the greatest. The cost of labour is associated with the payroll. The higher the salary, the more the workers will be motivated to contribute. Moreover, the quality of labour could be more important for the firms than its quantity.

It is also worth noting that the industry dummies in all groups and at each stage of the model showed joint significance. However, the regional innovation development

Table 7 CDM modelling for the Russian firms: third stage

Productivity	Total	Group 1	Group 2
Predicted logarithm of innovative sales	0.036**	0.0376**	0.0412*
	(0.0149)	(0.0174)	(0.0245)
Capital costs per employee	0.0524**	0.0406*	0.0595
	(0.0221)	(0.0218)	(0.0580)
Labour costs per employee	0.511***	0.526***	0.455***
	(0.0550)	(0.0609)	(0.116)
Index of innovation development	1.076	1.618*	0.484
	(0.708)	(0.884)	(1.279)
Industrial dummies	Yes	Yes	Yes
Adjusted R2	0.346	0.413	0.200

***Significant at the 1% level, **At the 5% level, *At the 10% level. The standard errors in parentheses. Group 1 contains low- and medium-technology firms ($N = 922$); and group 2 contains high-tech firms ($N = 642$)

index positively affects all groups of firms only at the second stage. It can be explained by the importance of a favourable innovation environment for a firm when introducing a new product.

4.2 Robustness check

Given the considerable regional differences in Russian territory, we consider the federal district fixed effects as the robustness check. Our first stage analysis demonstrates that all the slope coefficients are consistent in terms of sign and level of significance with the original findings. Nevertheless, the magnitude of the coefficients slightly changed due to the inclusion of district-level fixed effects. We exclude regional fixed effects due to a significant decline of the degrees of freedom of the estimator. Regarding the second stage estimation, findings obtained from the robustness check validate our original findings in terms of sign and significance level. Notably, the value of adjusted R2 slightly decreased since the coefficients of district fixed effects are insignificant. The third stage analysis considering the district fixed effects remains consistent with our original findings. The robustness checks considering district fixed effects affirm our assumption that the firms' location plays a minor role, unlike innovation intensity.

Obtained estimates of the first-stage model without the controls give us results very similar to the ones we previously presented, and the same indicators are found to be significant. Moreover, the values of the significant coefficients are also close to the ones observed in the original model.

The results in terms of significance and coefficient values are again similar to the original model at the second stage. However, the effect of predicted R&D expenditures is slightly higher for all subsamples. This may arise because predicted values are a bit different.

Table 8 Robustness check: first stage

The sum of R&D expenditures	Total sample	Group 1	Group 2
Size	1.831***	0.673	2.538***
	(0.343)	(0.599)	(0.361)
Age	−0.018**	−0.072**	−0.0083
	(0.008)	(0.031)	(0.008)
Competition	−0.010*	−0.000575	−0.012**
	(0.005)	(0.005)	(0.006)
Part of the larger enterprise	1.188***	0.952	1.072**
	(0.357)	(0.772)	(0.419)
Subsidies	0.159	0.822	−0.0313
	(0.449)	(0.810)	(0.472)
Taxes	−0.00668	0.0665	0.0178
	(0.392)	(0.626)	(0.457)
Inadequacy of the workers' specialisation	1.032***	1.298*	0.871***
	(0.320)	(0.691)	(0.321)
Import	1.242***	1.541***	1.070**
	(0.398)	(0.533)	(0.433)
Business licensing and permits	0.678**	0.500	0.754**
	(0.326)	(0.555)	(0.364)
Index of innovation development	1.406	−7.688**	5.048*
	(2.593)	(3.461)	(2.925)
Dummy North-Western	−1.249*	−1.250*	−1.964***
	(0.679)	(0.655)	(0.647)
Dummy Volga	−0.581*	−0.689	−0.514
	(0.345)	(0.634)	(0.388)
Dummy South	−1.050*	−1.307*	−1.797**
	(0.607)	(0.764)	(0.735)
Dummy Urals	−0.281	0.275	−0.0437
	(0.449)	(0.898)	(0.510)
Dummy North Caucasus	0.210	−2.087*	1.969*
	(1.074)	(1.176)	(1.022)
Dummy Siberian	−1.769***	−3.379***	−0.740
	(0.515)	(0.633)	(0.589)
Dummy Far Eastern	−0.968	−3.395***	0.640
	(0.901)	(0.763)	(0.976)
Industrial dummies	Yes	Yes	Yes
Wald test	14012.25***	4351.90***	4849.35***
Pseudo R^2	0.516	0.365	0.671

***Significant at the 1% level, **At the 5% level, *At the 10% level. The standard errors in parentheses. Group 1 contains low- and medium-technology firms ($N = 922$); and group 2 contains high-tech firms ($N = 642$)

Table 9 Robustness check: second stage

The logarithm of innovative sales	Total sample	Group 1	Group 2
Predicted sum of R&D expenditures	2.44e−07**	5.72e−07	1.90e−07*
	(1.03e-07)	(7.19e-07)	(1.01e−07)
Licensing	5.484***	1.385	9.715***
	(1.906)	(2.433)	(2.272)
Domestic suppliers	7.963***	9.349***	6.743***
	(1.116)	(1.455)	(1.665)
Foreign suppliers	6.161***	6.568**	5.911***
	(1.761)	(2.722)	(2.109)
Domestic consumers	10.09***	13.05***	8.401***
	(0.997)	(0.689)	(1.406)
Foreign consumers	10.80***	14.59***	8.430*
	(2.903)	(0.800)	(4.384)
Cooperation with universities	6.172***	7.090**	4.961**
	(1.851)	(2.961)	(2.309)
Training of personnel	1.189***	0.630	1.948***
	(0.345)	(0.429)	(0.572)
Index of innovation development	10.62***	9.127***	14.92***
	(2.585)	(3.318)	(4.316)
Dummy North-Western	−0.307	0.569	−0.912
	(0.664)	(0.884)	(1.000)
Dummy Volga	−1.694***	−1.162*	−2.295***
	(0.505)	(0.633)	(0.831)
Dummy South	−1.521**	−1.545*	−1.378
	(0.616)	(0.823)	(0.965)
Dummy Urals	−1.201	−0.835	−1.478
	(0.845)	(1.086)	(1.325)
Dummy North Caucasus	0.205	−0.227	1.029
	(1.143)	(1.308)	(2.117)
Dummy Siberian	−2.272***	−2.335***	−1.529*
	(0.488)	(0.587)	(0.920)
Dummy Far Eastern	−0.748	0.448	−2.824***
	(0.658)	(0.892)	(0.900)
Industrial dummies	Yes	Yes	Yes
Adjusted R2	0.175	0.163	0.185

***Significant at the 1% level, **At the 5% level, *At the 10% level. The standard errors in parentheses. Group 1 contains low- and medium-technology firms ($N = 922$); and group 2 contains high-tech firms ($N = 642$)

Table 10 Robustness check: third stage

Productivity	Total	Group 1	Group 2
Predicted logarithm of innovative sales	0.0397**	0.0372**	0.0487**
	(0.0157)	(0.0174)	(0.0242)
Capital costs per employee	0.0520**	0.0407*	0.0587
	(0.0220)	(0.0219)	(0.0579)
Labour costs per employee	0.508***	0.526***	0.453***
	(0.0548)	(0.0611)	(0.115)
Index of innovation development	0.781	1.623*	0.310
	(0.757)	(0.883)	(1.279)
Dummy North-Western	0.125	0.0887	0.213
	(0.163)	(0.187)	(0.287)
Dummy Volga	−0.0439	−0.136	0.333
	(0.113)	(0.142)	(0.211)
Dummy South	0.116	0.0942	0.250
	(0.190)	(0.174)	(0.364)
Dummy Urals	−0.0296	−0.106	0.381
	(0.174)	(0.183)	(0.485)
Dummy North Caucasus	0.397	0.400	
	(0.306)	(0.323)	
Dummy Siberian	−0.0974	−0.106	0.159
	(0.126)	(0.176)	(0.199)
Dummy far eastern	0.596**	0.677**	0.184
	(0.233)	(0.261)	(0.497)
Industrial dummies	Yes	Yes	Yes
Adjusted R2	0.348	0.413	0.206

***Significant at the 1% level, **At the 5% level, *At the 10% level. The standard errors in parentheses. Group 1 contains low- and medium-technology firms ($N = 922$); and group 2 contains high-tech firms ($N = 642$)

Finally, at the third stage, results are similar; the models are identical except for different estimates of the innovative sales. For this stage, the predicted innovative sales figures per employee are almost identical to those obtained in the unrestricted model. The finding suggests that the final effect of innovative sales on productivity is the same even without the control variables. Therefore, we can conclude that our results are robust.

4.3 Discussion

We confirmed that under given institutional conditions, a firm could improve its innovative activities through personnel training, cooperation with various organisations and R&D activities.

As for Hypothesis 1, we considered low-, medium-, and high-tech firms and confirmed that human capital affects the innovation activity of firms with different technological intensity differently. Our results show that at the stage of R&D, the quality of human capital has a positive and significant effect for the firms in both technological groups. In contrast, for the high-tech firms, the coefficient has a relatively higher significance. Training of personnel proved to have a positive and significant effect on the high-tech firms, as well as for the overall sample, at the stage of innovations.

As for Hypothesis 2, a regional innovative environment and all types of firm's cooperation were found to be significant and positive for the firms' innovations regardless of their technological intensity. This finding is in line with the literature (Fagerberg et al. 2010; Aldieri et al. 2018; Ramadani et al. 2019). Besides, the regional innovative environment appears to be positive and significant for R&D performed by high-tech firms. This can be explained by a relatively more important role of innovative climate for the activities of high-tech firms.

Besides, external sources of innovations such as competition and the ease of receiving business licenses and permits augmented firms' R&D expenditures. External sources are emphasised in the literature (Conte and Vivarelli 2014). Subsidies play an insignificant role in promoting R&D expenditures. Our finding echoes with Ramadani et al. (2019), who documented that subsidies play an insignificant role in augmenting R&D expenditures for transitional countries. Besides, Vakhitova and Pavlenko (2010) find a positive impact of state support on innovation expenditures but no effect on product or process innovations. The reason behind the controversial impact of subsidies might be specific features of institutions in the transitional economy of Russia (Ramadani et al. 2019), considering the importance of institutions for innovations (Lööf and Heshmati 2003).

Our investigation demonstrates that the firm imports, cooperation with foreign consumers, and foreign suppliers are driving factors to enhance R&D expenditures consistent with several prior studies (Lopez-Rodriguez and Martinez-Lopez 2017). The results show that R&D is positive and significant for innovations in the overall sample and for high-tech firms, implying a more substantial impact of R&D for firms with greater technological intensity, in line with the existing research (Ortega-Argiles et al. 2011; Gallié and Legros 2012; Teplykh 2018). Furthermore, a significant and positive impact of innovation on productivity is consistent with results from the literature (Hall 2011; Raymond et al. 2015; Morris 2018). However, we observe that the impact of innovation on productivity is more profound in high-tech firms.

In addition, our model considers a range of firms' characteristics. Firm's larger size and belonging to a larger enterprise positively and significantly affects R&D for the sample of all firms, and for high-tech enterprises, probably due to greater availability of resources for R&D. However, analysis of data shows that small and medium-sized firms eventually have the most significant innovative sales as a share of the revenue.

Data on innovations often impose limitations on the use of cross-section estimation (Roud 2007; Hall 2011, p. 12). At the same time, Morris (2018) points out that estimates based on cross-section data may be upward biased. With this accounted for, our estimates are lower than in other studies; this might be due to specific features of the Russian economy leading to lower returns from R&D expenditures. Roud (2007) highlights that the effect of R&D is positive and significant for Germany, Sweden and Russia. However, its magnitude is samller for Russia compared to the European countries. In the original paper on the CDM model, Crepon et al. (1998) considered the impact of R&D capital per employee on innovative sales. Crepon et al. (1998) observed that the coefficient of R&D is 0.431 in a basic model and 0.304 in the extended model based on French data.

Another reason for the lower coefficient can be differences in measurement: we consider the sum of R&D expenditures, not the R&D expenditures per employee. Besides, the differences in model specification and estimation methods can be the reason. Overall, the coefficient of the predicted sum of R&D expenditures is found to be lower than in literature, but the direction of the effect for the overall sample is in line with the findings of other authors (Vakhitova and Pavlenko 2010; Ramadani et al. 2019).

The impact of innovative sales per employee on productivity was found to be positive, between 0.04 and 0.05, for the whole sample and both groups of industries. The coefficient is slightly lower than in the literature on this stage, too, at 0.065–0.3 for developed countries (Crepon et al. 1998, p. 135; Lööf and Heshmati 2003), and 0.142 for Russia (Roud 2007). Besides differences in measurement, model specification, or estimation methods, this might result from specific features of the Russian economy, with productivity depending not only on innovations, but on the ability to work in a non-transparent institutional environment (Ramadani et al. 2019).

Our analysis confirms that innovations are a practical approach to increase productivity among Russian firms. In line with previous literature, this result is vital for Russia. However, the share of innovative firms is low, and many firms rely on non-competitive advantages or government support. Moreover, firms may be reluctant to innovate in the complicated institutional environment due to doubts about whether such actions will produce the desired effects.

At the same time, if we consider low-tech and high-tech firms separately, the connection between R&D and innovation is fully present only in high-tech firms. Therefore, high-tech firms should have an opportunity to spend more on R&D to improve their competitiveness; this depends on many factors, including the business environment and economic situation. Low- and medium-tech firms will be better off allocating their resources to alternative purposes and using external sources of innovations, such as cooperation with various organisations.

The Innovative Development Index proved to positively affect innovative sales of high-tech and low- and medium-tech firms. This index shows the importance of different aspects of the regional legislation, economic policy measures, and outcomes for innovative activity by individual firms, which underscores the necessity of improving the regions' innovative climate.

5 Conclusion

To shed more light on firm-level innovation and productivity in the transitional economy of Russia, we estimated the impact of R&D expenditures on innovation and labour productivity utilising the CDM model. The model was employed to analyse the firms belonging to industries with different technological intensity: high-tech, medium- and low-tech industries. To explain R&D expenditures and productivity nexus, we incorporate mediating role of innovations, personnel training, organisational cooperation, and regional technological advancement. Besides, we distinguished between the factors that can be influenced by the firm and the factors that the firm takes as given, for the case of Russian firms.

Our empirical investigation provides several findings. First, the results show that human capital is the key factor for promoting innovation, while its impact is conditional on the firm technological intensity. Precisely, high-tech firms benefit both from the quality of human capital at the R&D stage and from personnel training at the innovation stage. However, low- and medium-tech firms benefit from the quality of human capital at the R&D stage. Second, the striking finding is that both external human capital (the level of employees' qualification) and internal human capital (personnel training) proved to matter for a firms' innovation and productivity. Third, cooperation with various organisations along with a innovative regional environment plays a critical role for firms' innovation and productivity.

Although the impact of cooperation and regional innovative environment on innovations is sensitive to the firms' technological intensity, innovations proved beneficial for firms belonging to industries with various technological intensities. Even though spending on R&D insignificantly affect innovations in the low- and medium-tech firms, innovations positively affect their productivity. However, innovative projects are generally uncertain and risky, and even more so in an unfavourable business environment.

Our empirical findings draw several important policy implications. The positive and significant impact of human capital implies that both government and firms should contribute to human capital formation. Our findings are in line with the Russian government national development agenda aimed to enhance educational quality and R&D by 2030. Specifically, it is necessary to pay attention to fundamental science and education at the state level and aim education at the needs of innovative enterprises. The university graduates should meet the future job requirements. On their part, firms can organise a favourable working environment, training, and professional development for employees.

The positive and significant role of the regional innovative environment implies that economic policy should be aimed at developing a favourable business environment and decreasing barriers to innovation. Cooperation also proved to be meaningful for innovations and productivity; therefore, it should be promoted.

Overall, it is crucial to enhance human capital and firms' knowledge stock: improving the innovative environment, facilitating cooperation, particularly between the firms and universities, supporting training programs for the employees, and creating a framework for communication between the firms.

Our study has several limitations. First, the research was carried out based on cross-sectional data. At the same time, panel data would provide additional opportunities to apply more advanced econometric techniques and account for the innovation process's dynamic nature. Second, the study of specific policy initiatives aimed at human capital development and the improvement of the institutional environment for innovations would shed more light on developing the firms' innovation activities.

Among the other prospects for further research is studying the role of cooperation, state support, and property rights protection for firms of different sizes and industries. These issues may be significant for small and medium-sized firms in low- and medium-tech industries due to their relative shortage of in-house resources, as our findings suggest. Another area for further investigation is the role of a competitive environment and simplified bureaucratic procedures for innovative activities of start-ups and small and medium-sized firms. For now, we estimated competition only with several direct competitors, while careful examination of actual competition may offer more detailed results.

Acknowledgements The authors would like to thank the Russian Science Foundation for its support of the research project No. 19-18-00262 "Empirical modelling of balanced technological and socio-economic development in the Russian regions". We also express our sincere gratitude to the participants of the DEGIT Conference, Moscow (2018), particularly to Evguenia Bessonova, as well as to the participants of the Conference at the Graduate School of Economics and Management, Ural Federal University, Yekaterinburg (2018), particularly to Anna Fedyunina, for valuable discussion and suggestions.

Funding This study was funded by the Russian Science Foundation (Research project No. 19-18-00262 "Empirical modelling of balanced technological and socio-economic development in the Russian regions").

Declaration

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

References

Aldieri L, Sena V, Vinci CP (2018) Domestic R&D spillovers and absorptive capacity: some evidence for US, Europe and Japan. Int J Prod Econ 198:38–49

Avdasheva SB, Shastitko AE, Kuznetsov BV (2006) Competition and the structure of markets: what can we learn from empirical studies on Russia. Russ J Manag 4(4):3–22

Ayyagari M, Demirguc-Kunt A, Maksimovic V (2012) Firm innovation in emerging markets: the role of finance, governance, and competition. J Financ Quant Anal 46(6):1545–1580

Bartoloni E, Baussola M (2018) Driving business performance: innovation complementarities and persistence patterns. Ind Innov 25(5):505–525

Baum CF, Lööf H, Nabavi P, Stephan A (2017) A new approach to estimation of the R&D-innovation-productivity relationship. Econ Innov New Technol 26(1–2):121–133

Bozic L, Botric V (2011) Innovation propensity in the EU candidate countries. Transition Stud Rev 18:405–417

Brunow S, Birkeneder A, Rodríguez-Pose A (2018) Creative and science oriented employees and firm-level innovation. Cities 78:27–38. https://doi.org/10.1016/j.cities.2018.02.002

Caloghirou Y, Giotopoulos I, Kontolaimou A, Korra E, Tsakanikas A (2021) Industry university knowledge flows and product innovation: how do knowledge stocks and crisis matter? Res Policy 50(3):16

Carlino G, Kerr W (2014) Agglomeration and innovation. NBER working paper 20367

Cirera X (2015) Catching up to the technological frontier? Understanding firm-level innovation and productivity in Kenya. Innovation and entrepreneurship, trade and competitiveness global Practice. The World Bank 94671

Chudnovsky D, López A, Pupato G (2006) Innovation and productivity in developing countries: a study of Argentine manufacturing firms' behavior (1992–2001). Res Policy 35(2):266–288

Cohen WM, Levinthal DA (1990) Absorptive capacity: a new perspective on learning and innovation. Administ Sci Q Spec Issue Technol Org Innov 35(1):128–152
Conte A, Vivarelli M (2014) Succeeding in innovation: key insights on the role of R&D and technological acquisition drawn from company data. Empir Econ 47:1317–1340
Crepon B, Duguet E, Mairesse J (1998) Research, innovation and productivity: an econometric analysis at the firm level. Econ Innov New Technol 7(2):115–158
Gokhberg LM (2014) Rating of innovative development of the subjects of the Russian Federation. HSE, Release, Moscow, p 2
Gorodnikova NV, Gokhberg LM, Ditkovskii KA (2018) Indicators of innovation activity: 2018: statistical compilation. National Research University Higher School of Economics, NRU HSE, Moscow
Fagerberg J, Srholec M, Verspagen B (2010) Handbook of the Economics of Innovation 2. Chapter, Innovation and Economic Development, pp 833–872
Ferraris A, Santoro G, Bresciani S (2017) Open innovation in multinational companies' subsidiaries: the role of internal and external knowledge. Eur J Int Manag 11(4):452–468. https://doi.org/10.1504/ejim.2017.085583
Fonseca T, de Faria P, Lima F (2019) Human capital and innovation: the importance of the optimal organisational task structure. Res Policy 48(3):616–627
Gallié E, Legros D (2012) Firms' human capital, R&D and innovation: a study on French firms. Empir Econ 43:581–596
Griffith R, Huergo E, Mairesse J, Peters B (2006) Innovation and productivity across four European countries. Oxford Rev Econ Policy 22(4):483–498
Griliches Z (1979) Issues in assessing the contribution of R&D to productivity growth. Bell J Econ 10:92–116
Guisado-Gonzalez M, Vila-Alonso M, Guisado-Tato M (2016) Radical innovation, incremental innovation and training: analysis of complementarity. Technol Soc 44:48–54
Hall BH (2011) Innovation and productivity. NBER working paper no. 17178
Hall BH, Lotti F, Mairesse J (2013) Evidence on the impact of R&D and ICT investments on innovation and productivity in Italian firms. Econ Innov New Technol 22(3):300–328
Hatzichronoglou T (1997) Revision of the high-technology sector and product classification. OECD science. Technology and industry working papers no. 2
Haus-Reve S, Fitjar RD, Rodrıguez-Pose A (2019) Does combining different types of collaboration always benefit firms? Collaboration, complementarity and product innovation in Norway. Res Policy 48(6):1476–1486
Hewitt-Dundas N, Gkypali A, Roper S (2019) Does learning from prior collaboration help firms to overcome the two-worlds paradox in university-business collaboration? Res Policy 48(5):1310–1322
Krusinskas R, Norvaisiene R, Lakstutiene A, Vaitkevicius S (2015) Investment, Innovation and firm performance: empirical evidence from small manufacturing industries. J Finance Econ 3(6):122–131. https://doi.org/10.12691/jfe-3-6-3
Lööf H, Heshmati A (2003) The link between firm-level innovation and aggregate productivity growth: a cross-country examination. Res Eval 12:131–148
Lööf H, Heshmati A, Apslund R, Heshmati R (2001) Innovation and performance in manufacturing industries: a comparison of the nordic countries. SSE/EFI working paper series in economics and finance 457
Lööf H, Mairesse J, Mohnen P (2017) CDM 20 years after. Econ Innov New Technol 26(1–2):1–5. https://doi.org/10.1080/10438599.2016.1202522
Lopez-Rodriguez J, Martinez-Lopez D (2017) Looking beyond the R&D effects on innovation: the contribution of non-R&D activities to total factor productivity growth in the EU. Struct Change Econ Dyn 40:37–45
Masso J, Vahter P (2008) Technological innovation and productivity in late-transition Estonia: econometric evidence from innovation surveys. Eur J Dev Res 20(2):240–261
Marotta D, Mark M, Blom A, Thorn K (2007) Human capital and university-industry linkages' role in fostering firm innovation: an empirical study of Chile and Colombia. The World Bank
Martin BR (2012) The evolution of science policy and innovation studies. Res Policy 41(7):1219–1239
Morris DM (2018) Innovation and productivity among heterogeneous firms. Res Policy 47(10):1918–1932
OECD (2011) OECD reviews of innovation policy: Russian Federation 2011. OECD Publishing
Orlando MJ (2004) Measuring spillovers from industrial R&D: on the importance of geographic and technological proximity. Rand J Econ 35:777–786

Ortega-Argiles R, Potters L, Vivarelli M (2011) R&D and productivity: testing sectoral peculiarities using micro data. Empir Econ 41:817–839
Pakes A, Griliches Z (1984) (1984) Patents and R&D at the firm level: a first look. In: Griliches Z (ed) R&D, patents and productivity. Chicago University Press, Chicago
Prokop V, Stejskal J, Kuv'ıkov'a H (2017) The different drivers of innovation activities in European countries: a comparative study of Czech, Slovak, and Hungarian manufacturing firms. EkonomickyıCasopis 65(1):31–45
Ramadani V, Hisrich RD, Abazi-Alili H, Dana L-P, Panthi L, Abazi-Bexheti L (2019) Product innovation and firm performance in transition economies: a multi-stage estimation approach. Technol Forecast Soc Change 140(C):271–280
Raymond W, Mairesse J, Mohnen P, Palm F (2015) Dynamic models of R&D, innovation and productivity: panel data evidence for Dutch and French manufacturing. Eur Econ Rev 78(1):285–306
Roback P, Legler J (2021) Beyond multiple linear regression: applied generalized linear models and multilevel models in R. CRC Press, Boca Raton
Roper S, Love JH, Bonner K (2017) Firms' knowledge search and local knowledge externalities in innovation performance. Res Policy 46(1):43–56. https://doi.org/10.1016/j.respol.2016.10.004
Roud V (2007) Firm-level research on innovation and productivity: Russian experience,micro evidence on innovation in developing economies. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.596.8971rep=rep1type=pdf
Symeonidis G (1996) Innovation, firm size and market structure: Schumpeterian hypotheses and some new themes. OECD Economics department working papers 161. OECD Publishing
Solow R (1957) Technical change and the aggregate production function. Rev Econ Stat 39(3):312–320
Teplykh GV (2018) Innovations and productivity: the shift during the 2008 crisis. Ind Innov 25(1):53–83
Triguero A, Moreno-Mondájar L, Davia MA (2013) Drivers of different types of eco innovation in European SMEs. Ecol Econ 92(C):25–33
Vakhitova G, Pavlenko T (2010) Innovation and productivity: a firm level study of Ukrainian manufacturing sector, discussion papers 27, Kyiv School of Economics
World Bank (2019) World development report 2019: the changing nature of work. World Bank, Washington, DC. https://doi.org/10.1596/978-1-4648-1328-3. License: Creative Commons Attribution CC BY 3.0 IGO
Zemtsov S, Muradov A, Wade I, Barinova V (2016) Determinants of regional innovation in Russia: are people or capital more important? Foresight STI Governance 10(2):29–42. https://doi.org/10.17323/1995-459X.2016.2.29.42

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.