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Intangible assets and the efficiency of manufacturing firms in the age of digitalisation: the Russian case

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ABSTRACT

A wide consensus exists on the role of intangible assets in both developed and developing economies, especially now, with the new generation of information and communication technologies. Emerging economies generally demonstrate lower endowment with intangibles (Dutz et al., 2012), but follow the same positive patterns for long-run development. In Russia, the contribution of intangibles to growth is still modest, and its capacity to foster productivity has not been achieved. As previous studies showed, efficiency represents one of the main channels of total factor productivity growth. This paper studies the effects of intangibles on the efficiency of Russian manufacturing firms in 2009–2018. Considering the heterogeneity of sectors and firms, the stochastic frontier model is applied. In general, the impact of intangibles is positive but small and influenced by external shocks and structural features. The paper provides evidence on different contributions of intangibles to efficiency for high-tech and low-tech firms and its change over time. It contributes to the strand of literature regarding the technical efficiency measurement on the microlevel. On the practical side, the paper suggests an analytical framework for differentiated policy mechanisms to drive investments in intangibles, which are essential for current digital transformation.

KEY WORDS

intangible assets, technical efficiency, manufacturing, digitalisation

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Introduction

Intellectual capital endowment becomes a fundamental prerequisite for technological advancements across countries and industries. Intangible assets (IA) have been considered a main source of productivity on an aggregate level during the last decades (Aghion & Howitt, 2006; Ramirez & Hachia, 2008; Chun & Nadiri, 2016; Montresor &Vezzani, 2013).

In developed economies, the marginal contribution of intangible capital to output growth already

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exceeds the physical one in high-tech production industries (Marrocu et al., 2012). According to Dal Borgo et al. (2013), manufacturing is among the sectors most heavily invested in intangible assets in the UK (manufacturing accounts for 51% of intangibles contribution to growth). In the French production sector, the growth in the share of intangibles also contributes to its enlargement in other industries (Delbecque et al., 2015). In Germany, the investment in intangible capital grew by 80-89% of the physical capital's level during 1995-2006 and half of the overall investment in intangibles accounted for manufacturing firms (Crass et al., 2014). Similar tendencies manifest in China, where sectors with a higher share of investment in intangible assets were the most productive between 1999 and 2007 (Fleisher et al., 2015).

Such upswing was largely driven by information and communication technologies (ICT), which clearly manifested in the U.S. where after 1995, the contribution of intangibles to the GDP growth was equal to that of physical assets (van Ark et al., 2008; Corrado et al., 2009; Nakamura, 2010). The IT revolution of 1994–2005 saw the most significant impact of intangibles on economic growth (Brynjolfsson et al., 2017). The famous Solow paradox, addressing the absence of the effect made by new technologies on productivity, has been widely discussed in the literature that offers a set of explanations and evidence (David, 1991; Brynjolfsson, 1993; Hatzius & Kris Dawsey, 2015).

Currently, economies undergo changes due to the new generation of ICT, induced by a drastic advancement in computing power (Furman & Seamans, 2018). Digitalisation is interpreted as an introduction or significant expansion of digital technologies in an organisation, a sector or the whole economy, leading to changes in business processes and significant socio-economic effects. This is expected to result in productivity gains (Tambe & Hitt, 2014; Dedrick et al., 2013; Aboal & Tacsir, 2018), structural changes (Bogliacino & Pianta, 2016; Rasel, 2017; Neirotti et al., 2018), new business models (Teece, 2018) as well as innovation intensification (Kleis et al., 2013; Sun & Li, 2017).

National governments encourage companies to adopt digital technologies and heavily support such initiatives. Russia represents a good example of such a policy. The national programme "Digital Economy of the Russian Federation" has been introduced in 2019 to secure the digital transformation in main sectors. Will these measures lead to gains? As intangibles become the core of the industrial process, it is important to consider its current role, patterns of influence on Russian enterprises, and industry-specific and idiosyncratic differences of the firms.

Due to the different nature compared to the physical capital, the IA impact on firms' performance shows distinct mechanisms and channels, which are widely discussed in the literature. They may result in technological change, efficiency improvement, production factor reallocation or capital deepening (Bresnahan & Trajtenberg, 1995; Kumbhakar & Lovell, 2000; Chun & Ishaq, 2016; Nwaiwu et al., 2020). From the innovation side, they foster within and across industries spillovers (Bontempi & Mairesse, 2015; Thum-Thysen et al., 2017; Pieri et al., 2018) and provide an interplay across different types of intangibles.

A large strand of literature is dedicated to analysing different IA types on macro, sectoral and micro levels. On a country-scale, authors use a growth accounting framework to measure the contribution of intangibles to labour productivity, the total factor productivity and the economic growth calculation (Corrado et al., 2009; Fukao et al., 2009; van Ark et al., 2009; Borras & Edquist, 2013; Adarov & Stehrer, 2009; Apokin & Ipatova, 2017; Corrado et al., 2013; Thum-Thysen et al., 2017; Chen & Krumwiede, 2017; Rylková & Šebestová, 2019; Soltysova & Bednar, 2015).

Among BRICS economies, the Russian case is the least researched. Shahabadi et al. (2018) used the Solow residual (Solow, 1957) to estimate the impact of different types of intellectual capital on total factor productivity (TFP) in emerging economies, including Russia, and conclude that this group of countries acquired existing new technologies rather than developed them.

Based on the existing macro estimates for Russia (Voskoboynikov et al., 2020), the effects of intangibles are not as large in comparison with developed countries. ICT, as the main asset in the age of digitalisation, contributes little to the TFP growth of in comparison to other physical elements (machines, buildings, etc.). On the other hand, ICT-growth rate in 2002–2007 was the largest in manufacturing as in most dynamic finance and services (Voskoboynikov et al., 2020). Arguably, the capacity of ICT and other intangibles in Russian manufacturing was not fully exploited opposite to developed economies, did not achieve a threshold and might serve as a productivity driver in the next decades.

Only several studies exist regarding the role of intangibles on Russian microdata, which support

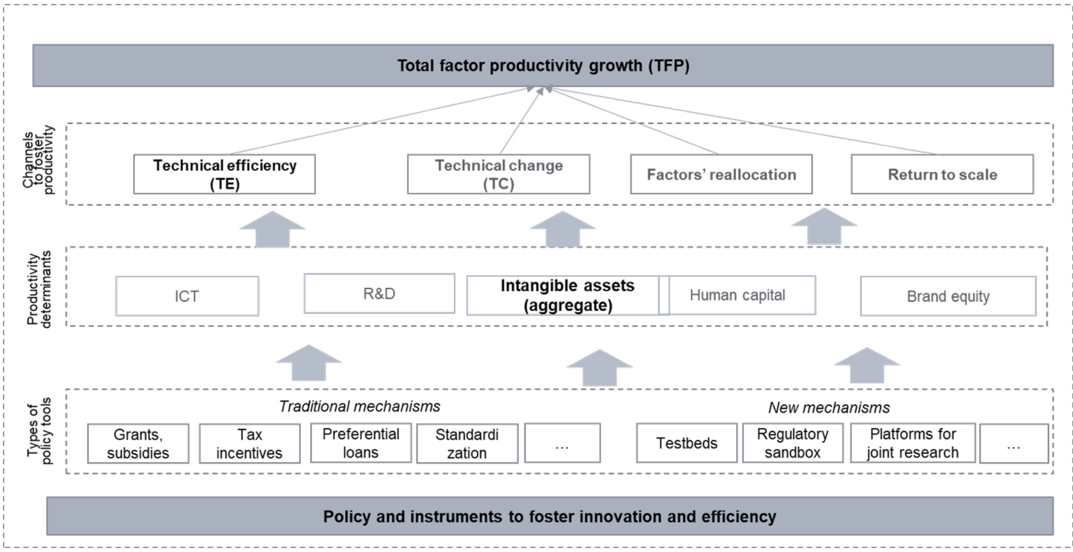

Fig. 1. Framework of the study in the context of productivity analysis

Source: elaborated by the author based on Kumbhakar and Fuss, 2000; Coelli et al., 2003; Corrado, Hulten and Sichel, 2005; Borras and Edquist, 2013.

evidence in the macrolevel. According to Shakina et al. (2014), a gap in intangibles is responsible for more than 26% of the variation in the gap in the economic value-added of Russian companies. Overall, the performance heterogeneity has a different scale of intangible capital in the firms (Molodchik et al., 2019). Several papers consider particular intangible assets and get similar patterns with other countries, particularly related to R&D and its link with technological change (Apokin & Ipatova, 2017; Pieri et al., 2018). Russian authors focus on company strategies for using IA (Shakina et al., 2016) and the taxonomy of firms based on this (Podmetina et al., 2011; Paklina et al., 2017), and addressing research and development in detail (Dezhina & Ponomarev, 2014; Simachev & Kuzyk, 2014; Gershman et al., 2018; Simachev & Kuzyk, 2019; Zemtsov et al., 2019).

According to previous results, efficiency was the main component of TFP, which has been affecting the productivity of industries since the end of 2000 (Ipatova, 2015) compared to the economic boom of 1998–2007 with a predominant role of the technological progress channel (Brock & Oglobin, 2018). Papers that refer to intangibles as an efficiency determinant of the level of firms are scarce. To close this gap, considering the evidence from the academic and empirical literature, this paper applied the stochastic frontier model (SFM) on the panel data for 2009–2018 of more than 300 public Russian companies from manufacturing industries. The following hypotheses were formulated: 1) intangibles positively affect technical efficiency and this effect increases over time; 2) IA with time become a major source of efficiency; 3) intangibles are more important for high-tech industries; and 4) its effects are reduced due to the crisis in 2014.

The paper is organised as follows. The first section briefly reviews the theoretical background of the paper. The second section reports on the empirical background. The third section describes the data of the study. The fourth section represents and discusses the results. The final fifth section gives policy implications and makes concluding remarks.

1. Theoretical background

This part overviews extant papers on IA and their relationship with productivity using microdata. This data-level enables using a broader set of intangibles concepts, variables and estimation techniques (Roth, 2019). To start, the outline of used IA definitions and that of the current study are given.

In financial accounting, an intangible asset is an object without a physical form that can bring economic benefits, when used in production activities for a long time. The academic literature considers intangible assets more broadly. They have key features, such as high value, a rarity for an organisation, complexity for imitation or substitution (Bontempi, 2016; Paklina et al., 2017). A comprehensive IA framework was proposed by Corrado et al. (2005) and is most often used in comparisons of countries and cross-countries. It includes research and development results, computerised information (software and databases), and economic competencies (particular characteristics of an individual firm, including personnel, trade names, etc.). An analysis is often stipulated by the availability and consistency of the data.

Most of the empirical results indicate a strong impact of IA on the efficiency of industrial companies regardless of country affiliation (Marrocu et al., 2012; Dal Borgo et al., 2013; Corrado et al., 2013; Goldar & Parida, 2017; Piekkola, 2020). Based on data of 1523 industrial enterprises located in key Chinese cities, Yang et al. (2018) found a significant positive relationship between the IA types (software, research and development, and organisational investment), and the performance of firms demonstrated differences in the relative importance of particular IA types compared with developed economies.

However, high investments in IA do not always lead to productivity growth: if a certain threshold is exceeded, further investments fail to generate positive effects. This relationship was found in public companies in Japan in 1991–2001 (Ramirez & Hachia, 2008). Companies from the industries of non-ferrous metallurgy and transport and telecommunications that reduced the volume of research and development, expressed in terms of capital stock, showed higher productivity. Two explanations are feasible: the IA distinct nature and lags to fully deploy and achieve effects. In general, IA act as a main source of productivity regardless of features particular to sectors and firms.

Long lags may lead to a negative impact on efficiency and productivity in the short term. Chappell & Jaffe (2018) found that IA investments lead to a decrease TFP caused by the time lag and cost growth of its implementation. Basu & Fernald (2007) obtained similar results when modelling the impact of ICT on industry productivity in the United States for 1987–2004. Short term investments may diminish TFP, as it needs time and resources for reorganisation and training. This lag can extend from 5 to 15 years. It also takes time to gain experience with a new production process. Over the long term, intangibles become particularly important for firms with initially low levels of productivity due to the catch-up effect (Heshmati et al., 1995; Castiglione & Infante, 2014).

The propensity to invest and the volume of investments in IA depend on internal characteristics of a particular firm, such as age and size, sector type and others (Marrocu et al. 2012; Goldar & Parida, 2017; Chappell & Jaffe, 2018; Yang et al., 2018). However, productivity is also strongly affected by external shocks. During these periods, even in the absence of significant changes in company strategies regarding IA, the rate of productivity growth may decrease (Tang & Wang, 2020).

Recent papers increasingly focus on the combination between different types of IA and its impact on performance through company innovation (Ramirez & Hachia, 2008; Kleis et al., 2012; Gómez & Vargas, 2012; Chun & Ishaq, 2016). Again, there is variation in the results. Montresor & Vezzani (2016) showed that IA is more important for the industry than internal research and development, which in turn is more important for the service sector. On the contrary, Ramirez & Hachia (2008) argued for a higher significance of internal R&D in manufacturing.

Thus, intangibles serve as an innovation factor (Hall et al., 2013), production factor (Corrado et al., 2009) or both (Pieri et al., 2018). Different types of IA may act as the first or the second category. Research is more important for innovation, while ICT — for productivity and efficiency (Hall et al., 2013); however, the former serves as a prerequisite of the latter two. Several papers also confirmed the role of R&D for efficiency gains (Ramirez & Hachia, 2008; Añón Higón et al., 2017; Shahiduzzaman et al., 2017). New waves of the literature suggest intangible assets contribute to service innovation in light of servitisation (Cheng & Krumwiede, 2017; Kozłowska, 2020) and business model transformation. Heterogeneity of results is often explained by individual characteristics of a firm (age, size, historical base of intangible assets, financial status, ownership, technology intensity, export status, and trade issues).

Based on the brief analysis, the IA assessment findings are rather diverse and depend on a large set of characteristics. This paper represents the first step to a wide analysis of IA features and trends in emerging countries on the example of Russian production companies.

2. Empirical approach

2.1. Model and method description

The empirical part of the research relies on the stochastic frontier model (SFM) as one of the most frequently used parametric methods in efficiency and productivity analysis (Coelli et al., 2003). The choice in favour of SFM is motivated by several reasons. According to Li (2009), production measurements are sensitive to selected techniques. Several studies have shown that the non-parametric DEA method can lead to unrealistic results, especially in a small number of observations and significant heterogeneity present in the current data. The key advantage of SFM is the absence of the assumption about the full efficiency of companies. Different levels of efficiency across companies, sectors, and countries explain the variation in TFP (Sharma et al., 2007). Moreover, in contrast to growth accounting and other non-parametric methods, SFM enables to reveal a causal relationship between productivity and various factors (Kılıçaslan et al., 2017).

SFM was firstly introduced by Aigner, Lovell and Schmidt (1977), and Meeusen and van den Broeck (1977), and ever since, it caught the attention of researchers in different domains, especially in the production analysis (Brasini & Freo, 2013; Chang et al., 2015). Conceptually, technical efficiency refers to the maximum achievable output with a given amount of input that changes under random (stochastic) forces (Farell, 1957). A frontier firm represents a best practice, which operates on the maximum available level of efficiency. A core feature of SFM is that it separates inefficiency from other random fluctuations and at the same time, it does not fix conditions between the elasticity of production and income shares (Castiglione, 2012).

A model for panel data was introduced by Kumbhakar & Sarkar (2003):

$$\ln y_{it} = \beta_{0t} + \sum_{j=1}^{k} \beta_j x_{it} + v_{it} - u_{it} \qquad (1)$$

where $\ln y_{it}$ — logged output, i=1,…, N — decision-making units (DMU), t=1,…T — time period, x_{jit}, j=1, …k — production inputs and other explanatory variables, v_{it} — exogenous stochastic noise, u_{it} — endogenous inefficiency error term.

Technical efficiency is closely tied with the productivity theory and contributes to TFP as one of the key transmission mechanisms (Pieri et al., 2018). When a firm improves its efficiency with existing technologies, it moves along the frontier. The adoption of new technologies may shift a frontier upwards due to technical change and transformation in the production process (Greene, 2008; Castiglione & Infante, 2014).

Inefficiency comprises two components of exogenous stochastic noise (v_i) and endogenous inefficiency error term (u_i) (Battese & Coelli, 1995; Kumbhakar & Lovell, 2000). The former is designed through heteroskedasticity equation, that might be estimated in one step by integrating it in production frontier or two-step approach, which means the consecutive estimation of two equations (Caudill & Ford, 1993; Battese & Coelli, 1995; Kumbhakar & Lovell, 2000). Consequently, factors can be studied that affect inefficiency and its intensity.

Most related studies use the translog specification of the stochastic frontier equation due to its flexibility and ability to measure the effect of changes in scale and allocative efficiency, as well as to identify time changing efficiency (Mattsson et al., 2020). However, several papers based on Russian data indicate the absence of an obvious advantage of the translog model over the Cobb-Douglas (Malakhov & Pilnik, 2013; Ipatova, 2015). Similar results were also obtained in the study by Shao and Lin (2002). Due to its simplicity, the Cobb-Douglas function represents a measurement of returns to scale and elasticity of substitution (Cardona et al., 2013).

SFM needs to impose distribution of error and technical inefficiency. It is assumed that the random error v_{it} is independent and identically distributed with zero mean and constant variance ($v_{it} \sim N(0, \sigma_v^2)$. The term u_{it} in the literature may have several types of distribution, while half-normal ($u_{it} \sim N+(0, \sigma_v^2)$) and truncated normal ($u_{it} \geq 0, \sim N+(\mu, \sigma_v^2)$) are most frequently used as indicators of time-varying technical inefficiency (Kumbhakar et al., 2017).

The current research uses panel data to discover the interplay between intangibles and inefficiency during ten years of accounting for the time trend. In the context of a broader approach of the TFP measurement, panel data enables to explore technical change as well and its evolution over time (Castiglione, 2014; Kumbhakar et al., 2017). The maximum likelihood method is used for estimation, as it is considered more informative than the general method of moments (Malakhov & Pilnik, 2013).

2.2. SFM in Russian Studies

Despite the wide use of SFM techniques, Russian researchers are discovering their advantages. There are several groups of papers that use SFM to examine inefficiency from different angles and factors. Manufacturing is the leader among the sectors investigated through a lens of SFM industries (Sabirianova et al., 2005; Ayvazyan et al., 2012; Mogilat & Ipatova, 2016). SFM was also used to estimate efficiency in banking (Kumbhakar & Peresetsky, 2013), non-profit organisations (Borisova et al., 2010) and some other industries.

Comparing different SFM models, three produce better results while considering heterogeneity and time trend: the four-error model, the True Random Effects (TRE) and time-variant models (TVD) (Malakhov & Pilnik, 2013). The level of data variability, the length of a panel, and the purpose of a study affect the choice of the appropriate model, but no single criterion applies in all cases. Shchetynin & Nazrullaeva (2012) obtained close results by testing five different models, starting from the basic one for panel data with constant (TI) and time-varying (TVD) technical efficiency. The most appropriate models with the distinguished inefficiency and individual effects are the true fixed-effects (Greene, 2008), the true random-effects and the model with four components (transient and persistent inefficiency) (Kumbhakar et al., 2014).

Different inefficiency patterns are attributed to a range of internal factors. Ipatova & Peresetsky (2013) used SFM to estimate the technical efficiency of production of rubber and plastic products. Controlling heteroscedasticity of the errors for 2006–2010, the authors focused on the return to scale and changes in technical efficiency during the crisis of 2008–2009. Both cross-sectional and panel data with Cobb-Douglas and translog specifications were tested for the sample of 1149 firms. It was shown that an increase in the size of a company raises its efficiency and return to scale. This result is robust for different functional types of production function and the evaluation method. In other words, the consolidation of enterprises may lead to the growth in average efficiency gains.

Shchetynin (2015) examined import effects on technical efficiency using SFM for the food industry. Four popular models were tested: time-invariant, time-variant, true random effects, and true fixed effects. The growth-share of import reduces technical efficiency but also results in a competition drop due to market concertation. Import growth helps to strengthen market positions of leading companies and hampers possibilities for the rest.

Several papers shed light on different determinants of technical efficiency. Krasnopeeva et al. (2016) investigated the impact of export status for manufacturing firms for 2004–2013. In doing so, they used two approaches based on SFM: the calculation of the marginal effect of the export status and the propensity score matching to compare similar exporting enterprises with non-exporters. Both approaches lead to the same result: the export effect does have positive implications. However, for the first approach, the average marginal effect for all industries and years was smaller and decreased after 2004. Technical efficiency and its marginal effect grow with the size of the firm.

Investments in fixed capital are another efficiency driver. Shchetynin & Nazrullaeva (2012) revealed a positive impact on the food industry in the period 2003–2010. While modelling the effects on cross-sectional and panel data, the translog specification is selected as more flexible possible changes in coefficients over time. The logarithm of investment in fixed capital with a year lag serves as inefficiency error; for the random error v_i a logarithm of labour costs was also applied. For those companies that invested in fixed assets in the previous period, the volatility of the inefficiency error was lower. Clustering firms by the number of employees they found that on average, technical efficiency estimates of the "true random-effects" model were somewhat similar in small and medium-sized enterprises. For large enterprises, the average value of technical efficiency was higher. In a model with two types of inefficiency (Kumbhakar et al., 2014), the distribution of technical efficiency estimates by clusters differed significantly. Overall, the results of modelling supported the hypothesis of a positive impact of investments; however, it is not always the case for the size. Technical efficiency of enterprises has gradually decreased since 2006. Large enterprises were the least affected during the crisis of 2008, they underwent a 2% decline in efficiency in 2010, while in the small and medium-sized enterprises, technical efficiency decreased by almost 7%.

SFM is also used as one of the parametric techniques to measure TFP in a number of papers. Ipatova (2015) provided evidence on the efficiency patterns for medium-tech industries and particularly for production of plastics and its TFP. On the panel of 2006–2012, SFM and DEA were applied for the efficiency measurement and robustness check. Differently than in other studies, Cobb-Douglas was chosen instead of translog, as there was no significant difference in the results. To compare the results of two models, the author used the Pearson correlation coefficient and the Spearman's rank correlation coefficient. Both DEA and SFM gave similar rankings of the firms, but the technical efficiency was different for the quantile groups of firms. The first quarter of the most productive firms demonstrated a positive trend in TFP and technical efficiency. Other 25% of firms were close to the level of 2006, and the remaining half of the sector showed weak results. Among different TFP components examined in the study, the technical efficiency demonstrated the highest variation and a drop in 2009. Its contribution and a technical change played the central role in TFP growth.

Apokin and Ipatova (2017) calculated TFP using SFM combined the Malmquist productivity indices with a technical efficiency component. Using the data of OECD countries and Russia for 1990–2010, they found that a higher TFP level was associated with a lower growth rate in the next period. Private R&D expenses were a significant factor for TFP growth, but with a lag of five years. However, for Russia, this influence was less due to a smaller share of private expenses in comparison with state expenses in the overall amount of R&D expenses.

Based on the description above, intangibles are not yet discovered as efficiency determinants; however, some studies account IA as a performance driver (Shakina et al., 2016; Molodchik et al., 2019).

3. Data and research design

This paper uses data from the Ruslana database for 340 public companies belonging to the economic activities listed under codes 10–33 OKVED2 (synchronised with the NACE classification). The time span covers 2009–2018 and includes 3310 observations. This category of companies makes a crucial contribution to productivity and overall investment. Previously, Paklina et al. (2017) also studied listed companies and assessed their strategic choices regarding intellectual capital.

Output as a dependent variable is presented by the operating revenue of companies. The number of employees (l) is measured in persons, while other explanatory variables, including fixed assets (fa), other assets (asset), intangible assets (ita), in thousands of Russian roubles. All monetary variables are nominated in constant prices of 2009 and deflated using the GDP index-deflators, which are calculated by the national statistical office and available on the website of the statistical office.

The main limitation of the study is the absence of data on ICT-capital at the level of firms. The aforementioned database contains data on R&D capital, but with numerous omissions that hamper estimation. To assess the intellectual capital of companies as a whole, the aggregate indicator of intangible assets is presented in the annual financial statements of the firms. IA has been previously shown as an adequate variable in the stochastic frontier exercises for Russian firms (Ayvazyan et al., 2012). According to the national accounting system, intangible assets comprise patent and other intellectual property on inventions, licenses on software and databases, trade names, as well as goodwill (KPMG, 2012).

As cited earlier, the Cobb-Douglas specification with logged values is chosen for Russian data. It is expressed as follows:

$$\ln y_{it} = \beta_0 + \beta_1 t + \beta_2 \ln fa_{it} + \beta_3 \, ln\, asset_{it} + \\ + \beta_4 ln\, ita_{it} + \beta_5 lnl_{it} + v_{it} - u_{it} \qquad (2)$$

where $ln\, y_{it}$— turnover of the company i in period t, t — years, $ln\, fa_{it}$ — fixed assets as proxy for capital, $ln\, ita_{it}$ — intangible assets, $ln\, l_{it}$— number of employees, v_{it} — stochastic noise, u_{it} — technical inefficiency. To include fixed capital that is rented by a company, and based on Ipatova & Peresetskiy (2013) and Shchetynin (2017), other assets ($ln\, asset_{it}$) are inserted in the model.

In this class of stochastic models, technical efficiency changes under determinants specified in the heteroskedasticity equation (Pieri et al., 2018). There are two determinants in the current study: intangible assets and the time trend. Intangibles also contribute to TFP due to the accumulation with time and technical change, which is embedded in the time trend t in the production frontier equation. The heteroscedasticity equation is defined as:

$$\log\,(\sigma_{uit}) = \delta_0 + \delta_1 ln\, ita_{it} + \delta_2 t \qquad (3)$$

where δ_n— estimated coefficients of technical efficiency determinants.

Following Pieri et al. (2018), it is assumed that TFP is influenced by the trend (t), intangible assets ($ln\, ita_{it}$), its evolution in time ($\rho_2 t \times ln\, ita_{it}$) and technical inefficiency (u_{it}):

$$tfp_{it} = \rho_0\, t + \rho_1 ln\, ita_{it} + \rho_2 t \times ln\, ita_{it} - u_{it} \qquad (4)$$

where ρ_{n}— estimated coefficients of TFP determinants.

Along with this, the time trend is usually interpreted as TFP in more common models for panel analysis (the time-variant model). To compare the trend attitude, two other specifications are applied: time-variant and time-invariant models. The first one estimates technical efficiency for each year separately. Such a model focuses on persistent inefficiency and does not require distributional assumptions (Kumbhakar et al., 2014). It has the following form:

$$\ln y_{it} = \beta_0 + \beta_1 \ln fa_{it} + \beta_2 ln\, asset_{it} + \\ + \beta_3\, ln\, ita_{it} + ln_4\, l_{it} + d\, year_{it} + v_i - u_i \qquad (5)$$

where $d\ year_{it}$ means dummy variables for each of ten years, other variables are the same as stated earlier. In contrast to the specification indicated in equation (2), the time-variant decay model assumes v_i and u_i to be independent. It also implies that there is a trend in inefficiency error, which is estimated in the following way (Kumbhakar & Lovell, 2000):

$$u_{it} = \left(-\exp\left(-\eta(t - T_i)\right)\right)u_i \quad (6)$$

where Ti — the last year in the panel, η — the decay parameter, errors v_{it} are independent and identically distributed with zero mean and constant variance ($v_{it} \sim N(0, \sigma_v^2)$, u_{it} is the base-level inefficiency (the level of inefficiency for firm i in the last period T_i) that follows truncated normal distribution ($u_i \sim N^+(\mu, \sigma_u^2)$), v_{it} and u_i are distributed independently. This helps to distinguish different patterns in trend and further discuss its possible reasons.

4. Empirical results

4.1. Intangibles and efficiency

This section presents the main results of the empirical analysis. As a preliminary step, it is checked whether SFM is an appropriate tool for efficiency estimation. In doing so, a simple regression model is estimated with an analysis of residuals distribution. It confirms the presence of heterogeneity and, thus, justifies the choice for SFM.

Main results are shown in Tables 1 and 2. The first contains the results of the estimation for the full sample of the firms. Four major models are tested. Model 1 demonstrates the estimation of the model without inefficiency determinants. Technical inefficiency induced by intangibles and the time trend is introduced in Model 2. Model 3 and 4 analyse effects before and after 2014. This year is marked as the cur-

Tab. 1. Panel Estimation of the Stochastic Production Frontier for the full sample of firms

	Model 1 (stochastic frontier without inefficiency determinants)	Model 2 (stochastic frontier with inefficiency determinants)	Model 3 (stochastic frontier with inefficiency determinants before 2014)	Model 4 (stochastic frontier with inefficiency determinants after 2014)
1. Production frontier (dependent variable ln_y)				
Number of observations	2,915	2,915	1,381	1,534
ln_fa_real	0.106*** (0.007)	0.106*** (0.007)	0.124*** (0.011)	0.096*** (0.009)
ln_assets	0.347*** (0.013)	0.354*** (0.013)	0.325*** (0.019)	0.381*** (0.018)
ln_l	0.561*** (0.016)	0.557*** (0.017)	0.507*** (0.026)	0.591*** (0.023)
ln_ita_real	0.019*** (0.006)	-0.011* (0.007)	-0.018 (0.011)	-0.023 (0.017)
t	0.016** (0.006)	0.017* (0.009)	0.008 (0.031)	0.082*** (0.024)
ita_t	-0.003*** (0.001)	-0.003*** (0.001)	-0.004 (0.004)	-0.001 (0.003)
const	4.732*** (0.136)	4.753*** (0.135)	5.294*** (0.201)	3.758*** (0.242)
2. Inefficiency equation (dependent variable)				
ln_ita_real_t		-0.108*** (0.011)	-0.178*** (0.021)	-0.065*** (0.013)
t		-0.002*** (0.016)	-0.177*** (0.066)	0.235*** (0.051)
const	0.072 (0.048)	0.362 (0.084)	0.806*** (0.137)	-1.583*** (0.403)
3. Stochastic noise (dependent variable)				
const	-1.495*** (0.058)	-1.424 (0.014)	-1.336 (0.074)	-1.447 (0.094)

Note: *, **, * * * — significance at 10%, 5%, and 1% levels, respectively; standard errors are shown in parentheses.

rency crisis and, according to the existent papers, should be the watershed in terms of efficiency and its changes (Bessonova, 2018).

Model 1 gives a general overview of the production frontier. Intangibles positively affect output; however, this value is still modest. The same is true for the time trend, which is interpreted as TFP in this specification. It means that during the period, an average firm in the sample improves its productivity. However, with time, intangibles produce a rather small effect on the production output. Such a result might be explained in several ways. Since intangible assets are expressed as accumulated capital (Corrado et al., 2009), it should depreciate and wear out, just as the physical does. Then, there is a need to update it and to expand its volume (Corrado et al., 2009; Bontempi & Mairesse, 2015). Capitalised intangibles as an aggregate indicator are an important factor for productivity. As determined by Bontempi & Mairesse (2015), capitalised assets give better results compared to those measured in costs, as conceptually they represent time-changing stock. Current results indicate that companies invest insufficiently in this type of assets. This statement is supported by sectoral statistics. Machines are considered the main source of innovation in manufacturing, and this trend has remained rather stable during the last decades (Gokhberg et al., 2020).

Model 2 has explicit efficiency determinants. There is a raise in the time trend for the end of the period, and its value is larger than in Model 1. The trend is small, but significant for efficiency improvement. Intangibles in Model 2 equation reduce technical inefficiency, as the corresponding coefficient is negative and strongly significant. By splitting the sample before and after 2014, one may see that the IA role as a production factor is not steady during the period. The declining trend is visible in the heterogeneity equation. Before 2014, the IA contribution to inefficiency was stronger (-0.18) than later (-0.07). This suggests that the positive process that started to emerge and previously gave positive outcomes, but is hampered by the crisis that corroborates the effects of several years. However, with time, the trend became positive and increased the output to roughly 1%. Why 2014 induces such unfavourable consequences for the companies? This year is associated with more expensive foreign technologies. This fact, however, is two-sided: on the one hand, firms were forced to develop solutions domestically and modify technological strategies. On the other hand, firms were unprepared for such a drastic change and suffered losses in the short run to adjust their behaviour (Bessonova, 2018). This influence was not the same across the sample.

Table 2 provides estimation for two groups of firms according to their R&D expenditures (firms that either invest in R&D and not) and the R&D intensity of the sector (firms that belong to high-tech and low-tech sectors), as manufacturing industries are very different in terms of technologies and resources used for innovation.

It is useful to indicate the patterns developed in these sub-groups of firms and how they differ from each other. For the sample of firms with R&D expenditures, intangibles affect technical inefficiency more than for those without, (-0.13) and (-0.1) accordingly. When considering high and low-tech industries, the results show the same patterns ((-0.26) and (-0.16) accordingly) and its the scale is bigger. The scale in the effect of intangibles on the inefficiency is biggest for the firms from high-tech sectors than for firms with R&D expenditures. One possible explanation is the systemic activities for knowledge accumulation that lead to additional gains from intangibles use in high-tech firms. This means that on average, such firms perform better and some complementarity between aggregate intangibles and systemic R&D activities may exist. A systemic activity for knowledge accumulation leads to additional gains from intangibles use in high-tech firms.

The effects of the trend are observed when considering the sub-sample of companies according to R&D expenditures. For these firms, the role of intangibles is more evident for the overall performance. To foster production, they rely more on IA that results in the technical change and shift of a frontier rather than gains in efficiency (Pieri et al., 2018). Firms without R&D do not seek to move the frontier upward and often use intangibles developed externally. The main channel of intangibles for them is tied with efficiency, not technical change and TFP (Bonanno, 2016; Kılıçaslan et al., 2017; Pieri et al., 2018).

Figs. 2–4 illustrate the distribution of technical efficiency for the full sample, and for two types of sectors, namely, high-tech and low-tech. It is obvious that low-tech firms reflect the higher distribution of efficiency, and generally, its level is smaller than in high-tech sectors, as well as dispersion. Higher variation of inefficiency means that companies have different patterns, and it is assumed that a group of leaders exists in both groups, and they do not approach each other. In other words, more efficient firms became even more efficient and enlarged the gap with the laggards.

The inefficiency dynamic shows several points to discuss (Fig. 5). Considering inefficiency changes over time, there is strong evidence that after a crisis year, the level of its spread should expand. The results suggest that the drop in efficiency appeared even earlier in 2013 and remained after 2015. This confirms that along with external shocks, more structural issues are responsible for the efficiency decline. The patterns are distinct for high- and low-tech firms. The latter underwent a larger drop in efficiency in 2015. In comparison with high-tech, its level is lower on average. It is important to note that technical effi-

Tab. 2. Panel Estimation of the Stochastic Production Frontier for sub-samples of firms by R&D expenditures and R&D intensity

	Model 5 (stochastic frontier for the firms of high-tech sectors)	Model 6 (stochastic frontier for the firms of low-tech sectors)	Model 7 (stochastic frontier for the firms with R&D expenditures)	Model 8 (stochastic frontier for the firms without R&D expenditures)
Production frontier (dependent variable ln_y)				
Number of observations	1,472	1,443	734	2,181
ln_fa_real	0.106*** (0.017)	0.112*** (0.007)	0.109*** (0.013)	0.076*** (0.007)
ln_assets	0.426*** (0.028)	0.332*** (0.015)	0.350*** (0.016)	0.397*** (0.019)
ln_l	0.599*** (0.034)	0.552*** (0.02)	0.531*** (0.023)	0.522*** (0.025)
ln_ita_real	-0.120*** (0.026)	-0.021*** (0.009)	-0.019** (0.009)	0.008 (0.008)
t	0.004 (0.048)	-0.015 (0.009)	0.026* (0.013)	0.021** (0.009)
ita_t	0.003 (0.004)	0.001 (0.001)	-0.0001 (0.001)	-0.004*** (0.001)
const	4.021*** (0.377)	5.082*** (0.149)	4.838*** (0.190)	4.922*** (0.17)
Inefficiency equation (dependent variable)				
ln_ita_real_t	-0.262*** (0.046)	-0.158*** (0.018)	-0.125*** (0.016)	-0.102*** (0.012)
t	0.296*** (0.057)	-0.112*** (0.023)	-0.008 (0.023)	-0.036*** (0.021)
const	-0.030 (0.495)	0.668*** (0.096)	0.373*** (0.119)	0.445*** (0.10)
Stochastic noise (dependent variable)				
const	-1.568 (0.111)	-1.315 (0.017)	-1.336 (0.065)	-2.082 (0.018)

Note: *, **, * * * — significance at 10%, 5%, and 1% levels, respectively; standard errors are shown in parentheses.

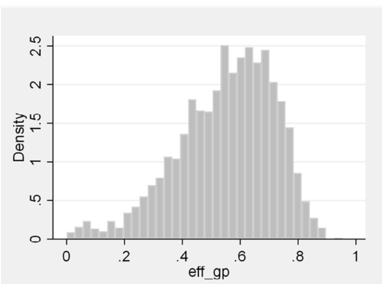

Fig. 2. Distribution of technical efficiency for the full sample with inefficiency determinants

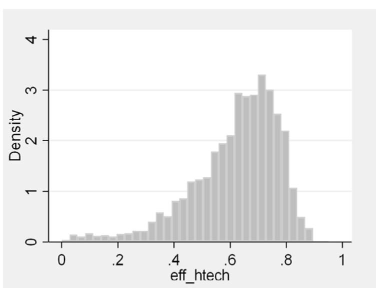

Fig. 3. Distribution of technical efficiency for the firms from high-tech sectors with inefficiency determinants

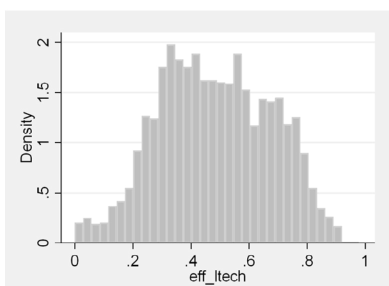

Fig. 4. Distribution of technical efficiency for the firms from low-tech sectors with inefficiency determinants

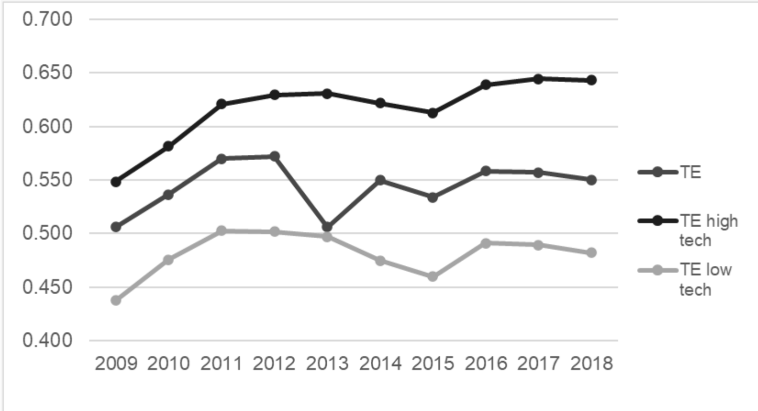

Fig. 5. Average technical efficiency dynamic in 2009–2018 for the full sample model

Note: TE — technical efficiency for the full sample, TE high-tech — technical efficiency for the firms of the high-tech sectors, TE low-tech — technical efficiency for the firms of the low-tech sectors.

ciency is a relative indicator and should be interpreted only in terms of ranking and its changes. Overall, the scale of technical efficiency, as expected, is stronger for high-tech industries. Studies for different countries also confirm such relationships (e.g., Crass et al., 2014; Añón Higón et al., 2017; Goldar & Parida, 2017; Piekkola, 2019).

4.2. Time trend analysis

To verify how trend and efficiency behave without intangibles as inefficiency driver, the paper analyses several sub-samples with time-variant (TI) and time-invariant (TVD) models, which also checks the robustness.

Table 3 shows the main results for the estimation of the impact made by the crisis year considering its changes and implications for firms of high- and low-tech groups. Different models — the frontier model without trend and inefficiency determinants and the time-variant model (TVD), which is more common for panel data and shows trends and technical efficiency changes — revealed a large difference and time-dependent change.

The significance of the years' coefficients is also tested. After 2014, high-tech firms experienced a reduction in production. In terms of the time trend, they performed better in 2011–2013. On the contrary, no significant changes were observed for low-tech firms for ten years. For the former, such a result is also revealed in Section 4.1 in the models with efficiency determinants, in contrast to high-tech firms. It means that a positive pattern started to emerge before the crisis and stopped in 2014. In 2014, import machines and equipment became more expensive and less available due to the national currency depreciation. As high-tech firms usually are more sensitive to import changes, they tried to substitute foreign technologies by developing them domestically (Simachev et al., 2019). It requires large resources that are taken away from current production and results in a decrease in output in the short run. In the medium run, the overall effect remains negative till 2018. This reasoning goes in line with past research in the field (Apokin & Ipatova, 2017). Due to enlarged spread across the firms in terms of inefficiency, an average firm did not succeed to grow, even though the frontier moved upwardly.

By further applying the TVD model for subsamples, a certain improvement in the output of low-tech firms is revealed, but inefficiency increased as well. It means that productive firms operate even better over time, while the laggards perform worse. The high-tech firms demonstrated the same pattern: technical inefficiency (the negative sign of the *eta* variable in Table 3) increased despite the trend growth, which is expected to result in negative growth for an average firm in the group.

A closer look at the period after 2014, which is the point of interest, reveals that trend changes, as well as efficiency *(eta)*, affected mostly the low-tech group. On the contrary, for companies from high-tech industries, the impact did not change significantly: almost the same contribution to reduction of inefficiency (-0.042) and production growth (0.014).

However, due to inefficiency expansion, the firms did not seize opportunities that opened with the frontier shift. Only a tiny group of companies improved their production possibilities. Due to difficulties with the technology transfer, companies were forced to seek other sources of technological solu-

Tab. 3. Estimations of time-invariant (TI) and time-variant (TVD) models by the two time periods and the groups of firms

	Model 1 TI-model without trend and inefficiency determinants for high-tech firms	Model 2 TI-model without trend and inefficiency determinants for low-tech firms	Model 3 TVD-model for high-tech firms	Model 4 TVD-model for high-tech firms after 2014	Model 5 TVD-model for low-tech firms	Model 6 TVD-model for low-tech firms after 2014
Production frontier (dependent variable ln_y)						
Number of observations	1,472	1,443	1472	770	1443	764
ln_fa_real	0.107*** (0.014)	0.073*** (0.007)	0.064*** (.018)	0.076*** (0.010)	0.047*** (0.016)	0.033** (0.014)
ln_assets	0.339*** (0.016)	0.430*** (0.019)	0.294*** (0.027)	0.462*** (0.029)	0.42*** (0.028)	0.311*** (0.030)
ln_l	0.552*** (0.023)	0.483*** (0.024)	0.642*** (0.038)	0.450*** (0.038)	0.558*** (0.032)	0.522*** (0.033)
ln_ita_real	0.010*** (0.004)	0.014*** (0.003)	0.014*** (0.005)	0.014*** (0.005)	0.004 (0.005)	0.005 (0.006)
t			0.071 (0.045)	0.039*** (0.008)	0.234*** (0.031)	0.016 (0.014)
const	4.542*** (0.202)	4.729*** (0.186)	6.148 (0.651)	4.281*** (0.284)	2.920*** (0.318)	6.878*** (0.336)
eta			-0.047** (0.019)	-0.042*** (0.012)	-0.240*** (0.022)	0.001 (0.012)
	-1.373*** (0.067)	-2.219 (0.102)				
	-0.136** (0.070)	0.116 (0.056)				

Note: *, **, * * * — significance at 10%, 5%, and 1% levels, respectively; standard errors are shown in parentheses.

tions, which, firstly, delayed production and, secondly, required the transformation in supply chains. Again, this goes in line with the literature that indicates that internal innovation activities have lagged effects and require time for accumulation to result in the output growth (Aghion & Howitt, 2006; Ramirez & Hachia, 2008, 2008).

To sum up, intangibles reduced the inefficiency, and this result was robust across time and groups of firms. After 2014, the IA impact reduced for the full sample, and at the same time, trend contributed positively to the overall output. Firms that belong to high-tech industries receive a greater IA effect on technical efficiency due to the existence of certain complementarity across different types of intangibles and stable accumulation of knowledge (Gómez & Vargas, 2012; Piekkola, 2019). However, testing intangibles impact on inefficiency with the simple time-variant model shows greater effects for low-tech firms. This may indicate that the models with heteroskedasticity equation are more suitable for measuring the relationship of intangibles and technical inefficiency. The finding represents an area for further exploration.

5. Suggestions for policy mechanisms to foster investments in intangibles

How to stimulate firms to invest in intangibles? Company incentives to invest in transformation and implement related complementary changes are largely affected by the policy to promote technology adoption, and this trend is stable across developed and emerging economies (Teece, 2018). Despite differences in the scope and direction of policies, almost all governments offer such support. It is not surprising that the industry receives attention, especially in times of crisis, when the modernisation of production becomes a factor of survival (Shakina & Barajas, 2016; Polder et al., 2018).

This statement is supported by the recent global crisis in 2008–2009. A trend was observed in developed economies to establish specialised institutions for the development and dissemination of advanced manufacturing technologies. Such initiatives were launched in the United States (sine 2011, the programme "Manufacturing USA"), the United Kingdom (since 2013, catapult centres), Australia ("Industry 4.0 Testlabs for Australia"), Canada (the Advanced Manufacturing Supercluster), Japan (Smart Manufacturing — Smart Monozukuri initiative), South Korea (manufacturing innovation centres 3.0) (GOV.UK, 2017; Australia Prime Minister's Industry 4.0 Taskforce, 2017; METI, 2017; Next Generation Manufacturing Canada, 2018; GAO, 2019). Most of these initiatives promote an advanced class of technologies, including computer modelling, new material development, production systems etc. that are expensive and need business restructuring (Nazarko, 2017).

Current trends in sectoral technological development are induced by the next wave of information and communication technologies (ITU, 2017; Brynjolfsson et al., 2017). Though the channels of technology dissemination and influence on production performance are common, digitalisation varies due to differences in countries and characteristics of firms. In emerging economies, productivity is frequently driven by the acquired and imported technologies, embodied in machinery and software. In general, they serve as a leading mechanism to promote innovation activities compared to domestic R&D in developed countries (Shahabadi et al., 2018). Recent studies show that the growth of ICT plays a key role in the TFP increase in emerging economies due to larger investments compared to other intellectual assets and primarily R&D (Shahabadi et al., 2018). In search of new innovation sources, digitalisation may play a role as a factor for production efficiency and the development of new products (Paklina et al., 2017).

To find appropriate triggers in sectors, a range of new policy mechanisms arises with the implementation of traditional ones. They contribute to narrowing the digital gap across and within sectors (Spiezia, 2011; Polder et al., 2018). The set of new tools comprises "living labs" (e.g., for driverless cars in Germany), testbeds (for blockchain technologies in the Republic of Korea) or platforms for joint research. Regulatory sandboxes is a relatively new tool that plays a particular role in industry absorbing new solutions. For example, special regimes help to test unmanned aerial vehicles in the US, or unmanned road vehicles in Germany (Federal Aviation Administration, 2018; BMWi, 2020). Many such initiatives address SMEs, including technology transfer, assistance with finding partners, and financial support (BMWi, 2019). Specialised platforms for small firms from different sectors provide an opportunity to choose an appropriate financial tool and receive professional consultation on digitalisation (France NUM, 2020).

Instruments aimed at promoting the demand for digital technologies also differ. Flexible fiscal mechanisms are applied to promote the mass adoption of technologies among companies. They cover a wide range of economic agents and include an accelerated depreciation or tax credits for investments in information technologies etc. Along with soft loans for buying digital products and services, various vouchers were actively used to support SMEs, including those focused on innovation (European Commission, 2018). Standardisation and certification is another area of interest to support the technology dissemination on a massive scale. Along with it, the entrepreneurship infrastructure, methodological recommendations for digital transformation, market regulation and other existing tools represent a large area for policymakers (OECD, 2017).

Aiming to maximise efforts of different decisions, requires them to be targeted in terms of sectoral problems and features, including efficiency and productivity issues. This is especially critical in the current times marked by the coronavirus crisis and challenges faced by countries. The national programme "Digital Economy of the Russian Federation" goes in line with the foreign initiatives and provides many mechanisms to support the adoption and use of digital technologies. The initiatives resemble those in other countries, where manufacturing is among the priority industries.

Results of the previous section suggest that intangibles do play an important role in decreasing the sectoral technical inefficiency. It is expected that intangibles in the short and medium run will secure an efficient production process, and later, it will contribute to the channel of innovation via the technological shift. Based on this reasoning, an analytical framework to choose policy instruments is introduced (Table 4).

Policy initiatives to promote digitalisation should be different due to sectoral R&D intensity and strategies to adopt digital technology, i.e., to develop or acquire. From this perspective, companies may introduce existing or new technologies. Several sets of policy tools can be distinguished. The number of R&D support tools is limited because of a risky

Tab. 4. Strategies and policy tools to support digitalisation according to the technology intensity of firms

	High-tech firms	Low-tech firms
Develop an intangible technology asset	*Effects* Frontier shift ++ Efficiency change - *Policy tools* Grants Venture capital Tax incentives Preferential loans Standardisation Testbeds Regulatory sandbox	*Effects* Frontier shift + Efficiency change + *Policy tools* Grants Tax incentives Preferential loans Standardisation Testbeds
Acquire an intangible technology asset	*Effects* Frontier shift - Efficiency improvement ++ *Policy tools* Tax incentives Preferential loans Technology transfer centres Guidelines and information platforms	*Effects* Frontier shift + Efficiency improvement ++ *Policy tools* Tax incentives Preferential loans Technology transfer centres Guidelines and information platforms

Note: The highlighted cells represent the largest effects for high and low-tech sectors; "+" reflects the intensity of the influence on technical efficiency or technical change (the frontier shift).

nature; however, they imply the most extensive effects in terms of efficiency and technical change. Low-tech firms that provide R&D obtain the same results, but they are less significant than high-tech. Again, a less intensive impact resulted from the acquisition of technological assets in low-tech firms. On average, it results in more considerable efficiency gains and is supported by instruments (tax incentives, preferential loans, transfer centres, etc.) that are expected to spread technologies in a large group of companies.

It is assumed that digital asset accumulation correlates with innovation capacity (Hall et al., 2013; Borgo et al., 2013; Añón Higón et al., 2017; Ejdys, 2020). Since then, an average firm has two alternatives: to develop a solution in-house or in cooperation with partners, including universities and scientific organisations. It may also choose acquisition from an external supplier. The previous studies found that high-tech firms more often adopting customised technological solutions or developing them in cooperation with external suppliers (Pieri et al., 2018). The opposite is true for low-tech firms, which frequently implement existing technologies. To support the development of new intangible assets, decision-makers may opt for more risky measures, such as venture capital, testbeds or regulatory sandboxes. The development of new technologies should reconcile with the elaboration of standards that offer new technical rules. When it comes to new solutions, the number of organisations is often limited, and in this case, grants or subsidies may be the most efficient way to stimulate innovation. As more firms get engaged in R&D, measures having a wider coverage are required, such as tax incentives (e.g., income tax relief for R&D activities). For all categories, regulation plays a central role as an enabler of legal conditions for technology adoption and use.

The acquisition has a relatively lower impact on productivity but may still result in the frontier shift. Policy instruments are less risky and aim to involve a larger number of firms. In the case of the purchase of new assets, a business often needs guidelines, frameworks and general information on new technological issues. Both for high-tech and low-tech groups, a similar set of instruments may be applied. The initial idea of such support is to smooth differences in technological capacities and stimulate within and across industry spillovers.

The reasoning presented in this section represents a starting point to a further, more detailed investigation of types of intangibles and the scale, to which they affect manufacturing companies in Russia. Here, only some general vision is developed. Such an approach enables better planning and assessment of technological development in organisations (Bieńkowska, 2020; Nazarko et al., 2020). Next research may address the empirical estimation of different types of intangibles and the impact associated with this policy instrument on the propensity of companies to accumulate intangibles. This may bring useful insights into fostering investments in intangibles and, particularly, digital technologies.

Conclusions

The role of intangibles in the digital economy is growing rapidly in emerging and developed countries. In Russia, they have not yielded productivity gains despite the rapid upsurge of the IT industry (ISSEK HSE, 2020). Several structural features may be responsible for such a situation. Studies in the area on a company level are scarce; however, they may shed light on some reasons for the current low impact of intangibles on productivity and growth.

The current paper enlarges the extant empirical literature by revealing the role of intangibles in emerging economies. In particular, it contributes to the strand of productivity analyses and efficiency as its key component, including patterns and its development over time. It also accounts for differences in sectors due to research intensity and gives special attention to the crisis period. This may be of significant interest in the discussion on post-pandemic economic development and appropriate tools for it.

Focusing on listed companies from the manufacturing sector, the stochastic frontier model is applied to estimate the role of aggregate intangible assets as a determinant of technical efficiency. Its role as a production driver is still modest due to low investments and the level of accumulation (Shakina & Molodchik, 2014; Shakina et al., 2016; Paklina et al., 2017). Firms from high-tech sectors enjoy more extensive effects of intangibles on inefficiency decrease. After 2014, this effect was lower than before.

The consequences of the crisis were significant for all groups and widened the gap within and across the high-tech and low-tech firms. Consequently, a small subgroup of most efficient units improved its level, while others worsened their position. The dynamics of the indicator in low-tech firms reflect the increase in inefficiency due to higher dispersion.

Such disproportions have a structural nature and should be addressed with appropriate policy tools. To secure systemic investments in intangibles and digital technologies as its major component, national governments have adopted sets of measures, especially during the last years (OECD, 2019). Sectoral and time features of firms, as well as the actual endowment with intellectual capital, should be considered while designing policies.

The paper offers an analytical framework to select relevant policy tools to foster corporate investments in the development or acquisition of intangible assets. In-house research implies targeted measures, while in the case of acquisition, instruments with large business coverage are required. Both types are important to accumulate the domestic intellectual endowment and on the other hand, to adopt existing frontier technological solutions.

This approach is reasonable to consider since the share of Russian organisations engaged in technological innovation remains low. To achieve a large scale of technology adoption, small and medium companies should largely implement and use different digital solutions in technological, organisational and other domains, and restructure all business processes. Along with the problems of underinvestment in innovation, firms do not fully see the advantages of digital technologies. It is important to provide communication and financial tools to scale up domestic technologies and contribute to their dissemination across industries.

The current study has several limitations. First, due to the lack of data, only the general aggregate effects of intangibles were considered. Second, it does not account for other determinants, which are captured in the time trend. The further elaboration on these problems represents a large area for investigation in the field of productivity analysis in Russian firms.

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