National Research University Higher School of Economics

as a manuscript

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PRODUCTIVITY DIVERGENCE AT THE FIRM LEVEL

PhD Dissertation Summary
for the purpose of obtaining academic degree
Doctor of Philosophy in Economics

Academic supervisor:

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JEL: D24

Moscow – 2022

Motivation

As economic growth slows in both developing and developed countries the economic literature focuses on productivity as a potential source of intensive growth of the economy.

In this study, several performance indicators on the firm level are analyzed. *Labour productivity, total factor productivity (TFP) and technical efficiency* are used as measures of firms' performance.

Labour productivity reflects how productively a single factor, labour, is used to generate output. In this study, labour productivity is computed as a relationship between a measure of revenue or value added and that of the number of a firm's employees. Total factor productivity (TFP) reflects how productively combined inputs are used to generate output. In this study, labour and capital are used as combined inputs and value added as a measure of output. *Technical efficiency* is estimated using the stochastic frontier analysis (SFA) and reflects the distance between the firm and the production frontier.

These measures of a firm's performance are not independent. TFP may be viewed as one of the labour productivity's driving forces, while technical efficiency may be seen as a factor of both labour productivity and TFP.

According to numerous studies, growth in labour productivity and TFP have slowed dramatically after the 2008–2009 crisis. These trends are visible on both the aggregated and firm level.

Some papers view growing inequality among enterprises in terms of labour productivity (or TFP) as the main factor behind a slowdown in their growth (Akcigit and Ates, 2019). According to this hypothesis, growth rates at the production frontier remain high. The cause of the aggregate slowdown in productivity growth is change in the performance of firms operating at a distance from the production frontier rather than right at the frontier.

A firm-level data analysis allows studying not only changes in average productivity in an individual industry but also those in the whole distribution: whether there is productivity convergence or divergence.

Russia is also experiencing a slowdown in economic growth. As in other middle- and higher-income countries, there is limited scope for expansionary acceleration through employment growth and capital buildup. On the one hand, according to demographic forecasts, extensive population growth is hardly to be expected. On the other hand, a sufficient amount of capital has already been accumulated. Therefore, this study focuses on the sources of intensive growth enabling the effectiveness of using production factors already available to be enhanced.

However, as in other countries, productivity growth in Russia has slowed in recent years. According to official statistics, since 2009 labour productivity has shown significantly slower growth at the aggregate level than in the early 2000s.[1] Moreover, the years 2015–2016 saw labour productivity decline in Russia.

Acceleration of labour productivity growth can arise from several sources. Firstly, the reallocation of resources among sectors, for example, the flow of labour between the industrial and services sectors or between the formal and informal sectors of the economy. Secondly, the reallocation of resources among firms within industries, and thirdly, individual firms' productivity growth. This study puts emphasis on the second and third factors, i.e., on the analysis of intra-industry changes of labour productivity and TFP.

Thus, the study of the labour productivity (and TFP) heterogeneity in Russia contributes to the literature on the potential for accelerating economic growth. One measure that government programs propose in order to help increase labour productivity growth is to enhance the contribution of small and medium-sized enterprises (SME) to value creation.

However, according to studies based on firm-level data (Andrews et al., 2016), labour productivity is higher at larger firms. A number of papers suggest that young enterprises show fast productivity growth, while not all SMEs are young and fast-growing (Haltiwanger et al., 2013). Therefore, the analysis of the sources of fast productivity growth at the lower bounds of the productivity

[1] https://rosstat.gov.ru/accounts

distribution is relevant to assessing the potential for reducing the distance to the production frontier.

Significant changes in the distribution of labour productivity (or TFP) may occur during crisis periods. On the one hand, the least productive firms may be forced to reduce output or even exit the market, which may stimulate the reallocation of resources towards more efficient companies. On the other hand, a rise in uncertainty may hamper the establishment of new companies and young firms' growth. There are various government programs to support employment during the crisis. Consequently, the number of low-productivity companies in the market may increase, since companies that would leave the market under normal circumstances may continue their operations thanks to financial assistance. Therefore, assessing the impact of government employment support programs on resource reallocation is highly relevant.

Brief literature review

The issues of productivity heterogeneity, in other words, the convergence of output levels were initially addressed in cross-country studies. As microdata becomes more available, the within-industry heterogeneity also attracts growing interest of researchers. Empirical studies based on firm-level data show a wide dispersion of labour productivity levels not only across countries, but also within narrowly defined industries even in a single country (Syverson, 2011).

Studies based on micro-data from OECD countries (Andrews et al., 2016) show that there is a wide gap between the productivity leaders and the rest of firms, with this gap having grown in recent years. Evidence suggests that the production frontier continues to expand, at least in the services sector. Thus, the authors assume that a slowdown in TFP growth at the macro-level after the 2008–2009 crisis stems not so much from slowed technological progress as from rising heterogeneity within narrowly defined industries.

According to one of the hypotheses, an increase in productivity dispersion within industries is owed to a decline in the intensity of knowledge diffusion from the frontier firms to the rest of companies (Akcigit et al., 2019). Lack of access to knowledge hampers laggards' productivity growth. The authors stress that the growing role of digital technologies, including the use of tacit knowledge, as well as big data, may cause distortions to the flow of knowledge among firms.

A set of papers (Andrews et al., 2016; Cette et al., 2019) show that the widening of productivity gap between leaders and laggards is accompanied by a negative correlation between growth in productivity and its initial level (also referred to as β-convergence in the literature). The authors show that the speed of convergence has weakened since 1997.

The high rates of productivity growth of the least productive firms can be owed to the age structure of firms. According to several studies (Haltiwanger et al., 2013), young firms are extremely important for job creation, they contribute disproportionately to the US economy's net growth. Since the productivity level of entrants tends to be lower than that of incumbents, the contribution of young firms is found at the bottom of the productivity distribution Thus, the concentration of high-growth firms among the least productive ones arises from the fact that young firms are reaching full production capacity during their first years in the market. The authors emphasize that the role of the small firms of all ages is less important than that of young firms entering the market.

According to the literature (Andrews et al., 2016), labour productivity and firm size are positively correlated, as more high-productivity firms accumulate resources and expand, while laggards remain small. In this regard, one of the factors hampering the efficient allocation of resources among companies may be the relatively low exit rate of low-productivity companies.

An increase in the number of market exits stimulates the reallocation of resources towards the most productive companies (there is a so called "cleansing effect") only if the least productive companies exiting the markets are replaced by new companies with growth potential. However, in the 1979 – 2013 period in the United States the worsening of the economic situation had a faster effect on the number of market entries than on the number of market exits (Tian, 2018). However, a decrease in the rate of market entries (the "scarring effect" of the crisis according to Ouyang (2009)), along with an increase in the number of exits of young companies, impacts future economic growth negatively, because it slows the reallocation of resources from exiting companies to new ones, and, consequently, growth potential of young organizations fails to be realized.

The economic literature shows that one of the causes behind the long-lasting presence of low-performing companies in the market may be easy access to financing during the periods of low interest rates on loans and weak economic growth. Under these conditions, banks may lack motivation to enforce the liquidation of a company, although in the absence of financial support an enterprise would go bankrupt. In the literature, these enterprises are known as zombie firms (Caballero et al., 2008). The probability of zombification may rise in periods of massive government financial support in response to the crisis arising from the coronavirus pandemic, since such support may prompt distortions to resource allocation in favor of less productive companies (Lalinsky and Pá, 2021).

According to the literature (Voskoboynikov, 2017), the efficient reallocation of resources along with the development of institutional environment that promotes technology diffusion among firms is essential to reducing a significant gap between productivity leaders and the rest of companies in Russia (Bessonova, 2018).

Productivity heterogeneity in Russia as one of the key aspects of economic growth is the subject of a number of papers which apply the stochastic frontier analysis (SFA). This method assumes that it is possible to identify an individual industry’s production frontier which reflects the maximum possible output for a given quantity of resources (Aigner et al., 1977). Firms in the industry operate at some distance from the frontier. The greater the distance to the production frontier, the lower the technical efficiency of a firm.

Using the SFA, the authors of several studies (Ipatova and Peresetsky, 2013) show that the technical efficiency of firms producing rubber and plastic products declined after the Great Recession (2008–2009). The productivity heterogeneity increased in this industry as a consequence of the crisis. Technical efficiency was highly stable, indicating how difficult it is to close the gap with the leaders.

The goal and objectives of the dissertation research

The goal of this study is to assess changes in the heterogeneity of labour productivity (or total factor productivity) and technical efficiency in Russia in response to the worsening of the economic situation after 2014 and to the shock of the crisis caused by the coronavirus pandemic. To address this goal, the following objectives were set:

- using data on Russian firms, to estimate the relationship between the level of labour productivity (or total factor productivity) and growth in the relevant indicators, in other words, to estimate the speed of β-convergence;
- to identify the source of rapid growth in labour productivity at the bottom of the distribution;
- to determine the nature of rapid growth in labour productivity at the bottom of the distribution, the moment and causes of a growth slowdown;
- to estimate TFP growth at the production frontier and changes in the productivity gap between the leaders and the rest of enterprises within narrowly defined industries;
- to estimate changes in the dispersion of technical efficiency of firms during the sample period, taking into account the correlation between the dispersion of technical efficiency and the size, as well as the age of firms;
- in the context of the crisis triggered by the coronavirus pandemic, to determine the relationship between the rate of market exits and the level of productivity, i.e., to analyze whether there was potential for the “cleansing effect” of the crisis, as well as to assess change in the rate of market entries as an indicator of the “scarring effect” of crisis;
- to identify the impact of the subsidized lending programs as a support measure during the coronavirus-triggered crisis on access to financing, depending on firms’ level of labour productivity.

Methodology

The study relies on the firm-level data of Russian companies from the Bureau van Dijk's Ruslana database: financial variables, the number of employees, and the registration date. In addition, value added is computed as the sum of labour costs and revenue less total cost; and labour productivity is computed as the ratio of value added or revenue to the number of employees.

Nominal variables, excluding the non-current assets, are deflated by gross value added deflators, which are available at the large sectors level, and the producer price index in three sectors (mining and quarrying, and utilities), which are available mainly at the level of 2-3-digit of Russian Classification of Economic Activities (OKVED/OKVED2) codes. Non-current assets are deflated by the fixed asset price index calculated as the ratio of the fixed asset value index to the volume index.

The sample period is not the same in all papers, the differences are presented in the first row of Table 1. In the two papers (Bessonova and Tsvetkova, 2021; Bessonova et al., 2020) the sample period is 2011–2016. In another paper (Bessonova et al., 2021a), the sample is updated and extended until 2018. In the other two papers (Tsvetkova, 2021; Bessonova et al., 2021b), the updated sample is limited to 2013–2018 and 2018, respectively.

Due to the poor quality of the data, firms with fewer than 10 employees are excluded from the analysis. In the paper by Tsvetkova (2021), the sample is limited to organizations with more than 50 employees (row 2, Table 1).

Table 1. Key characteristics of the data and methodology used

		Do productivity laggards ever catch up with leaders? (Bessonova and Tsvetkova, 2021)	Opportunities for accelerating labour productivity growth: The role of small and medium-sized enterprises (Bessonova et al., 2020)	Technical efficiency trends of Russian firms in 2013–2018 (Tsvetkova, 2021)	Market exits during the pandemic (Bessonova et al., 2021a)	Productivity and lending during the pandemic (Bessonova et al., 2021b)
Sample period	(1)	2011-2016	2011-2016	2013-2018	2011-2018	2018
Number of employees	(2)	>10	>10	>50	>10	>10
Sector coverage	(3)	Some sectors are excluded	Some sectors are excluded	Some sectors are excluded	-	-
Sample size	(4)	339 047	339 047	205 107	457 196	352 373
Number of narrowly defined industries	(5)	173	173	105	290	290
Classification of economic activities	(6)	OKVED	OKVED	OKVED2	OKVED2	OKVED2
Output	(7)	Value added	Value added	Revenue	Revenue	Revenue
Production frontier	(8)	Computed, model	Computed	Model	Computed	Computed
SFA – production frontier specification	(9)	Translog, frontier fluctuates in time	-	Cobb-Douglas function	-	-
SFA – technical efficiency specification	(10)	Technical efficiency is independent of firms' characteristics	-	Technical efficiency depends on firms' characteristics	-	-

Source: author's own elaboration.

In several papers (Bessonova and Tsvetkova, 2021; Bessonova et al., 2020; Tsvetkova, 2021) firms from some sectors are excluded from the analysis: agriculture, construction, financial activities, education, healthcare and public administration (row 3, Table 1). Estimation of production functions in these sectors requires special methods of analysis that take into account the features of output and resources in these sectors. In addition, in the paper by Bessonova et al. (2021a) the operating enterprises (as of April 2021) and those that exited the market before 2017 are also excluded. The total number of observations is presented in the fourth row of Table 1.

The samples are divided into narrowly defined industries according to their main numerical code of OKVED or OKVED2 (row 6, Table 1). As a result, the number of narrowly defined industries in the papers ranges from 105 to 290 (row 5 of Table 1).

Within the narrowly defined industries, outliers are defined as 0.5% of observations with maximum and 0.5% with minimum values of the main financial indicators and the number of employees. Observations with a maximum of 0.5% labour productivity values are also classified as outliers.

Labour productivity measures are calculated as the ratio of value added or revenue to the number of employees (row 7 of Table 1). In the paper by Bessonova and Tsvetkova (2021), TFP is also used as an indicator of a firm's performance. It is calculated as $TFP = \frac{VA}{K^{\beta}L^{\alpha}}$, where VA is value added, L is the number of employees, and K is the amount of non-current capital.

The coefficients α and β are estimated by two methods. Under the first method, α is calculated as the average share of labour costs within narrowly defined industries. Under the second method, α and β are estimated using the approach proposed by Wooldridge (2009) as the elasticity of value added with respect to labour and capital, respectively, where value added may be represented via production function $VA = A(K^{\beta}L^{\alpha})$. Under this method, labour is an endogenous variable, since a firm can hire more employees expecting high demand. Therefore, this factor of production is instrumented by capital, as well as a polynomial of the third degree in two variables: lagged capital and lagged volume of materials used.

Within each narrowly defined industry, the production frontier, which hereinafter is referred to as computed, is determined as the median value of labour productivity (or TFP) among the top 5% of the most productive companies. Then the firm's distance to the computed production frontier is determined (row 8 of Table 1).

Within each narrowly defined industry, firms are divided into deciles according to their distance to the production frontier, as well as into three broader groups: leaders, followers, and laggards. Productivity leaders are the top 20% of the most productive enterprises in each industry. Followers are firms whose performance is below that of the leaders but above the median. Laggards are the firms whose performance level is below the median.

Productivity deciles, as well broader groups (leaders, followers, and laggards), are relative indicators. Therefore, unlike absolute productivity measures, they do not reflect differences between sectors (industrial firms are on average more productive than firms in the services sector). In addition, the use of such relative indicators also helps avoid the bias associated with the different distribution of labour productivity within the industry. Therefore, this makes it possible to consider firms from the tenth decile as the most productive and firms from the first decile as the least productive, regardless of industry in which they conduct business.

Labour productivity deciles in 2018 are used as a performance indicator in the paper by Bessonova et al. (2021b). The data on deciles is combined with that from Bank of Russia form 0409303 "Information on corporate loans" for 2019–2020. The paper analyzes the scope of changes in total lending and in the number of loans in 2020 depending on the level of the labour productivity decile.

In the paper by Bessonova et al. (2021a), data on three broad labour productivity groups (leaders, followers, and laggards) is combined with data on the status of a firm from SPARK-Interfax, including the date of market exit. The paper analyzes how the rate of market exits in response to the shock of the coronavirus pandemic differs depending on a firm's relative level of labour productivity.

In the paper by Bessonova and Tsvetkova (2021), the 90-to-10 ratio, i.e., the ratio of the level of labour productivity of the 90th percentile to the 10th percentile, is used as an indicator of the heterogeneity of labour productivity in each industry.

According to studies on β-convergence in other countries (Andrews et al., 2016; Cette et al., 2018), Bessonova and Tsvetkova (2021) estimate its speed in Russian industries. The base specification is as follows:

$$\Delta lp_{it} = \beta_0 + \beta_1 gap_{it-1} + \beta_3 \ln(age)_{it} + \sum_{p=2}^{3} \beta_p * G_p + \sum_{j=2013}^{2016} \beta_j * Y_j + \sum_{k=2}^{8} \beta_k * S_k + \varepsilon_{it},$$

where Δlp_{it} is growth in labour productivity, gap_{it-1} is the distance to the computed production frontier in the previous period, $\ln(age)_{it}$ is the firm's log age, and G_p, Y_j и S_k – a set of dummy variables for the size, year and sector, respectively. Several alternative specifications are also estimated, including interactions between the distance to the computed production frontier and age, size, labour productivity growth (or TFP) at the computed production frontier.

To estimate heterogeneity changes from the perspective of technical efficiency the SFA method is used. This method allows the production frontier model and the distance to the frontier (row 8 of Table 1) to be estimated simultaneously. Two main specifications of the model are used in the study. In the first specification, Bessonova and Tsvetkova (2021), apply the production frontier model with a translog specification (row 9 of Table 1):

$$y_{it} = \beta_0 + \beta_1 l_{it} + \beta_2 k_{it} + \beta_3 t + \beta_4 l_{it}^2 + \beta_5 k_{it}^2 + \beta_6 t^2 + \beta_7 l_{it} k_{it} + \beta_8 l_{it} t + \beta_9 k_{it} t + v_{it} - u_{it},$$

where y_{it} is the logarithm of value added, l_{it} is the logarithm of the number of employees, $k_{it}$is the logarithm of capital used, v_{it} is the error term, $v_{it} \sim N(0, \sigma_v^2)$, $u_{it} \geq 0$ represents technical inefficiency, $u_{it} \sim N^+(0, \sigma_u^2)$. The technical efficiency index $TE = E\{e^{-u_{it}} | v_{it}\}$ and ranges from 0 to 1, where 1 means the maximum technical efficiency (the production frontier) and 0 means to the minimum technical efficiency.

The inefficiency error specification has the following structure: $u_{it} = G(t)u_i$ (row 10 of Table 1). Two alternative functions are used as $G(t)$: $G(t) = e^{\gamma(t-T)}$ and $G(t) = \left[1 + exp(\sum_{j=2012}^{2016} \beta_j * Y_j)\right]^{-1}$, where T is the last period in the sample, γ is the convergence coefficient, Y_j is a dummy variable for jth year, where j ranges from 2012 to 2016. The first function $G(t)$ assumes its monotonic change during the sample period. The second function $G(t)$ assumes fluctuations in technical efficiency from year to year during the sample period.

This first specification of the production frontier model allows Bessonova and Tsvetkova (2021) to estimate the rate of TFP growth as the sum of three components: change in the production frontier, change in technical efficiency, and economies of scale. The TFP growth rates thus obtained for two types of technical efficiency functions, $G(t)$, are comparable with the computed growth rates of labour productivity for the same period. The monotonous technical efficiency model, however, smooths out fluctuations and does not reflect a slowdown in the decline of TFP in 2016.

The second specification of the production frontier is used in the paper by Tsvetkova (2021), and its functional form is Cobb-Douglas (row 9 of Table 1):

$$y_{it} = \beta_0 + \beta_1 l_{it} + \beta_2 k_{it} + \beta_3 othAs_{it} + v_{it} - u_{it},$$

where y_{it} is the logarithm of revenue; l_{it} is the logarithm of labour costs; k_{it} is logarithm of capital used; $othAs_{it}$ is logarithm of other current assets; $v_{it} \sim N(0, \sigma_v^2)$ stochastic noise; $u_{it} \sim N^+(0, \sigma_{u,it}^2)$ inefficiency error.

The form of the inefficiency error is more complex than in the first specification of the production frontier model and takes into account correlation between technical efficiency and size and age of a firm, as well as change in technical efficiency over time. The base specification is as follows:

$$\ln\left(\sigma_{u_{it}}^2\right) = \delta_0 + \delta_1 \ln(\overline{emp_\iota}) + \delta_1 \ln(\overline{age_\iota}) + \gamma_0 after14,$$

where $\overline{emp_i}$ is the average number of employees in a firm during the sample period; $\overline{age_i}$ is the average age of a firm during the sample period; $after14$ is a dummy variable for the period after 2014.

Key findings

1. The speed of β-convergence is estimated based on the regression analysis performed in the paper by Bessonova and Tsvetkova (2021). The farther from the production frontier a firm operates, the higher its labour productivity (or TFP) growth. The rate of β-convergence decreases with higher growth rates of TFP at the production frontier, while small and young firms show higher rates of β-convergence.
2. Bessonova and Tsvetkova (2021) find that despite the evidence of β-convergence in most industries during the sample period from 2011 to 2016, there was no σ-convergence, as evidenced by an increase in the 90–to–10 ratio. The widening of the gap stems not so much from rapid growth of productivity leaders, as from a decrease in labour productivity of the rest of companies. While the most productive firms do not increase their productivity, a sharp jump of this indicator through introducing new technologies (including digitalization, the relevance of which is only increasing) is difficult to achieve without a set of measures encouraging firms to improve production efficiency.
3. Bessonova et al. (2020) show that the main source of rapid labour productivity growth is a small group of young enterprises that are just entering the market. Productivity growth rates are higher among the youngest companies, but their share in the sample is small. In this group, rapid growth is mostly due to the catching up: young firms are working to reach full production capacity. After the second year in the market, new firms catch up with the average productivity of incumbents, with labour productivity growth slowing significantly. At the same time, the growth rates of labour productivity in the group of small enterprises of all ages are on average no higher than in the group of large companies.
4. Bessonova et al. (2020) also show that the effectiveness of quantitative

measures seeking to increase the number of SMEs, as well as support for particular high-growth firms, may not be sufficient to significantly accelerate the economy at large, since high rates of productivity growth rapidly peter out. Comprehensive measures providing for the efficient reallocation of resources, including the removal of obstacles to the market exit of low-productivity companies, the improvement of employee retraining programs, and the development of the bankruptcy system can help achieve the goal of accelerating aggregated economic growth. At the same time, measures to create conditions for growth of high-efficiency companies, including creating a favorable business climate and promoting competition, can also play an important role.

5. SFA results presented in Bessonova and Tsvetkova (2021) show that the majority of industries in the sample suffered a technical efficiency decrease in the 2011–2016 period. In industries showing an insignificant change in technical efficiency, growth at the production frontier was slower than in industries where technical efficiency was declining. Thus, in some sectors the heterogeneity of firms remained at a stable level due to a sluggish rise at the frontier rather than to laggards' strong catch-up growth.
6. Estimation results of SFA models with heterogeneous technical efficiency presented in Tsvetkova (2021) suggest that a firm's technical efficiency increases with a company's size and declines with age. Estimates of technical efficiency changes bear out the findings that most of the industries did not improve this measure of firm performance over the 2013–2018 period. Some industries showed a technical efficiency decline, with the lowest values posted in 2015–2016, whereas the years 2017–2018 saw a recovery of technical efficiency. Since technical efficiency decreased in large industries, their contribution to the total revenue and the number of employees in the sample exceeds 50%.
7. Bessonova et al. (2021a) show that during the crisis arising from the coronavirus pandemic the rate of market exits was the highest in the group of

productivity laggards. The results of the analysis suggest the evidence of the "cleansing effect" of the crisis. On the other hand, the impact of the "scarring effect" is also found, since there was a sharp decrease in the number of new companies entering the market.

8. An analysis of changes in lending in 2020 against a background of the coronavirus pandemic, shows that the number of loans issued expanded significantly compared with 2019 due to the launch of subsidized lending programs offering low interest rates (Bessonova et al., 2021b). However, despite a large number of subsidized loans, total lending at subsidized rates in 2020 did not exceed the levels of subsidized lending in 2019. Also, the structure of unsubsidized lending remained almost unchanged: banks issued loans to the most productive companies more often, with total lending to these firms exceeding that to less productive companies.

Contribution

1. The study combines two approaches used in the literature to analyze the productivity heterogeneity: β-convergence and gap to the production frontier. In the latter case, the papers by Bessonova and Tsvetkova (2021) and Tsvetkova (2021) apply the SFA technique. The study shows β-convergence in terms of labour productivity and TFP in the sample of Russian firms, in line with results for other countries (Andrews et al., 2016). According to the estimates obtained, the speed of β-convergence is lower than in the sample of French firms (Cette et al., 2018).
2. The results of stochastic frontier models estimation presented in Bessonova and Tsvetkova (2021) and Tsvetkova (2021), indicate no growth in technical efficiency in 2011–2018, which is consistent with earlier findings in the literature showing a drop in this indicator during the crisis period of 2008–2009 (Ipatova and Peresetsky, 2013). The analysis by Tsvetkova (2021) confirms the conclusion about a positive correlation between a firm's size and its technical efficiency (Krasnopeeva et al., 2016) not only for industry, but also for most Russian sectors.

3. In this study, the analysis of labour productivity heterogeneity in part relies on the literature on a firm's life cycle. The estimates in the paper by Bessonova et al. (2020) based on Russian firm-level data corroborate the conclusion about the key role of young firms among fast-growing companies rather than small companies of all ages (Haltiwanger et al., 2013). The increase in labour productivity in this group is due to catching up, since the productivity level of new companies is on average lower than that of the incumbents.
4. The study contributes to the literature on the effectiveness of government support in response to the crisis caused by the coronavirus pandemic. Bessonova et al. (2021a) and Bessonova et. al. (2021b) show that in Russia, as in some other countries (Lalinsky and Pá, 2021), the shock of the pandemic and the response measures did not lead to a significant reallocation of resources towards low-productivity companies, including through easier access to credit. The "scarring effect" of the crisis, which brought about a drop in new market entries and a rise in the exits of young companies, is more relevant to Russia.

List of the author's original papers

Bessonova E., Tsvetkova, A. (2021). Do Productivity Laggards Ever Catch Up with Leaders? *Review of Income and Wealth*. (Scopus Q2)

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