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Widening the productivity gap in the Russian economy in 2009–2015: Stochastic frontier analysis using firm-level data☆

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Abstract

This paper analyzes total factor productivity (TFP) in Russia over 2009–2015 using firm-level data. Stochastic frontier analysis is employed to simultaneously estimate TFP growth and the distance to the production-possibility frontier for each firm in the sample. The results suggest significant positive rates of technological progress; however, the gap between technological frontier firms and laggards widened over the entire period under consideration. Consequently, most sectors experienced negative average TFP growth in 2009–2015. Technology diffusion from leading to less efficient firms in Russia remained limited, resulting in persistently low average productivity growth. Although the market share of less efficient firms shrank over time, these firms did not exit the market, leaving scarce resources trapped in inefficient production. To accelerate TFP growth, it is essential to create conditions that encourage the quicker exit of inefficient firms. This can be achieved by simplifying bankruptcy procedures, shifting government support from distressed to expanding enterprises, and reducing unreasonable administrative barriers.

Keywords: total factor productivity, TFP growth, stochastic frontier analysis, productivity gap, technology diffusion.
JEL classification: D24.

1. Introduction

Downward trends in Russia's GDP growth during the pre-pandemic period have revived discussions about potential sources of sustainable economic growth.

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In the early 2000s, Russia's economy expanded primarily due to favorable oil price dynamics. However, after the 2008–2009 global financial crisis and before the COVID-19 pandemic, positive GDP growth rates were observed only briefly, followed by a slowdown across nearly all sectors of the Russian economy, resulting from both internal and external factors. Experts broadly agree that intensive growth fueled by oil and gas exports has reached its limit, and future economic progress should rely on technological advancement and higher efficiency of production factors. Calculations for the Russian economy based on aggregated data (Voskoboynikov, 2017) show that, starting from 2010, both labor and total factor productivity (TFP) growth rates have been slowing.

Studies examining post-2009 productivity dynamics using microdata point to slower growth rates in both developed and developing economies. For instance, Andrews et al. (2016) analyzed OECD countries and found a generalized deceleration in productivity growth and stagnation in manufacturing. Similarly, Brandt et al. (2022) used Chinese data to identify a decline in TFP growth after 2007, attributing this trend to reduced firm dynamism.

The stylized facts from studies on productivity divergence during the period between the two crises of 2009 and 2020 (e.g., Andrews et al., 2016) could be summarized as follows:

- technological progress occurred only among the most productive firms operating on the technology frontier;
- the diffusion of new technologies from leaders to less efficient firms was limited, likely due to a declining ability of the latter to adopt innovations;
- inefficient firms did not exit the market, with aggregate productivity growth slowing down as a result.

One possible explanation for these trends is that the mechanism of inefficient firms' exit and new firms' entry might have changed. Indeed, a large share of inefficient firms operating in an industry could, first, directly reduce average TFP or labor productivity in the industry and, second, impede the entry of new firms, which are potentially more innovative and could show a high level of post-entry growth (Cette et al., 2018; Bartelsman et al., 2013). The misallocation of production factors and the locking-in of scarce resources in inefficient firms eventually lead to the crowding-out of more innovative firms from the market. Thus, Andrews et al. (2016) show that the productivity gap had significantly widened since the global financial crisis, peaking in 2015.

Recent research on productivity trends in Russia also reveals a pronounced decline in TFP and labor productivity growth, particularly after the global financial crisis (Blöechliger and Wildnerova, 2020; Abramov et al., 2023). Blöechliger and Wildnerova (2020) further report that Russian enterprises consistently lag behind European counterparts in productivity. Firm-level analyses confirm that TFP growth is significantly lower in small businesses than in larger firms (Kislitsyn and Orekhova, 2019). Additionally, Kaukin and Zhemkova (2023) show a marked decrease in resource allocation efficiency in 2012–2018. Thus, the Russian economy features a significant gap in the productivity and efficiency of enterprises within individual industries. The question therefore arises as to what extent a lack of reallocation of resources from less efficient to more efficient enterprises, both between and within industries, has been constraining Russia's technology-driven economic growth.

This study explores Russian productivity trends from 2009 to 2015 using firm-level data. This timeframe is chosen for two main reasons. First, much of the productivity economics literature concentrates on secular stagnation occurring between the global financial crisis and the COVID-19 pandemic. Second, a stable sample — necessary for identifying industry leaders — is available for this period. This sample also supports consistent micro-level measurement of key indicators, including value added, employment, and capital.

The study aims to evaluate how Russia's productivity trends compared to global patterns and to identify the unique characteristics of Russian firms during this period. Firm-level TFP growth is estimated using stochastic frontier analysis (SFA), allowing simultaneous assessment of productivity growth rates and the distance to the technological frontier for each firm. This enables us to analyze productivity trends demonstrated by technology leaders and less efficient firms in individual sectors over 2009–2015 and the impact of divergence in these trends on overall TFP growth.

The paper is organized as follows. Section 2 reviews the literature. Section 3 describes the methodology and data used. Section 4 presents the results of the stochastic estimation of the production possibility frontier and TFP trends. Section 5 concludes.

2. Related literature

The economic literature has extensively discussed the slowdown in productivity growth between the 2008–2009 global financial crisis and the COVID-19 pandemic. For example, two surveys by the OECD and the IMF examining productivity growth trends reveal a slowdown in productivity growth among technology leaders at both the country and firm levels. The IMF (2018) report stresses that the diffusion of advanced technologies to emerging market economies accelerated productivity growth in these countries and supported cross-country income convergence. By contrast, the OECD survey (Andrews et al., 2016), looking at TFP trends within an economy, finds that the mechanism for diffusion of advanced technologies from leaders to laggard firms changed, while the productivity gap between these two groups in OECD countries had been widening since 2000. A number of studies also show a similar trend toward increasing productivity dispersion within industries (Berlingieri et al., 2017, for the OECD; Decker et al., 2018, for the United States; Gamberoni et al., 2016, for the EU).

Earlier studies suggest that high turnover rates of firms in a particular industry boosted efficiency in individual industries (Syverson, 2011). This upturn became possible because less efficient firms exited the market, whereas among entrants, those demonstrating higher growth rates survived. Thus, the economic research suggests that, over the period before the global financial crisis, mechanisms of creative destruction supported efficient market growth, at least in the most advanced economies. Developing economies showed similar trends, despite institutional environments that sometimes prevented them from being fully realized.

Using data from Thailand for the period from the late 1980s to early 1990s, Aw et al. (2001) find that the contribution of new firms and the exit of inefficient firms to the overall productivity growth rate in an industry could reach 50%. Rawat and Sharma (2021) analyze data on Indian manufacturing firms over 1999–2018, dif-

ferentiating between persistent and transitory inefficiencies. Their results suggest that firms with persistent inefficiencies exit markets faster, while firms with transitory inefficiencies exhibit beta convergence, improving productivity and catching up with industry leaders. Hence, industry structure is heterogeneous: some firms are able to bridge productivity gaps, although not always quickly enough, while others are forced to exit markets in a fairly competitive environment. Research on China's economic growth before the global financial crisis suggests that it was driven not only by substantial capital investment but also, to a large extent, by rising TFP (Zhu, 2012; Brandt et al., 2012, using firm-level data in manufacturing over 1998–2007). Thus, during the period before the global financial crisis, emerging economies were also undergoing creative destruction to a certain extent.

More recent research has increasingly focused on the misallocation of resources in developing countries and the locking-up of resources in inefficient firms. A number of studies on China have documented a slowdown in aggregate productivity growth in the aftermath of the global financial crisis. The impact of the crisis itself on China's economy was short-lived, but microdata on manufacturing after 2011 show a significant slowdown in growth, with some studies even recording a decline in the average growth rate of TFP in manufacturing over 2011–2012 (Cao and Mao, 2022; Cerdeiro and Ruane, 2024).

Other studies suggest that resource misallocation was a drag on China's and India's economies even during periods of high TFP-driven growth (Hsieh and Klenow, 2009; Song et al., 2011). Hsieh and Klenow (2009) examine the efficiency of resource allocation in China and India and estimate how much these economies would have grown had the distribution of resources between efficient and inefficient economic agents been comparable with that in advanced economies, such as the United States.

It is worth noting that studies on resource misallocation in two large developing economies, China and India, on the one hand, find that efficiency losses in both countries were quite high, while on the other hand, the institutional sources of misallocation were completely different. Research on China attributes a significant portion of productivity losses to a large share of state-owned enterprises in the economy (Dai and Cheng, 2019; Brandt et al., 2022). Significant investments in these enterprises somewhat reduce incentives for private-sector development and mitigate the positive effects of creative destruction. Research on India has focused on the presence of an informal sector in the economy and institutional constraints on small business growth and its transition to the formal sector in explaining resource misallocation (Alfaro and Chari, 2014; Mohommad et al., 2021).

Resource misallocation is a problem not only for emerging markets but also for developed economies. Estimates by Calligaris (2015) for Italy show that resource misallocation led to a significant slowdown in TFP growth during 1993–2011; moreover, the contribution of this factor to the slowdown in productivity growth increased over the period under review. Fernald and Li (2022) argue that US productivity growth was very moderate between 2004 and 2019. Kehrig (2015) finds that, during economic slowdowns in the United States, dispersion of productivity growth among individual firms increased — a pattern that Fernald and Li (2022) interpret as evidence of the absence of a crisis "cleansing" effect, in which recessions typically weed out less productive firms and reallocate resources to more efficient ones, thereby improving aggregate productivity.

Thus, between the two economic crises — the global financial crisis of 2008–2009 and the atypical crisis provoked by the COVID-19 pandemic — research on productivity trends discussed declining growth rates, with many studies attributing this deceleration to weaker firm turnover dynamics and the persistence of a significant number of inefficient producers in the market. The COVID-19 crisis reopened this debate. On the one hand, the shock was assumed to force out a considerable number of inefficient companies from the market, activating the cleansing effect of the crisis. On the other hand, large government injections through business support programs in developed countries created a risk that inefficient companies would remain in the market for a long time.

An interesting result was obtained by Bloom et al. (2025) in estimating the primary effects of the COVID-19 crisis in the United Kingdom. They find that TFP declined by 5% within firms due to rising costs and capacity underutilization. Still, the authors reveal opposing trends associated with the crisis cleansing effect: during the COVID-19 period, the largest negative effect was concentrated in low-performing sectors, and ultimately, the least productive firms within them had to exit the market. As the least productive players ceased operations, the overall negative effect on aggregate productivity was not as strong.

Research on productivity trends in Russia also suggests a slowdown in productivity growth, which became more pronounced around the global financial crisis. Blöechliger and Wildnerova (2020), examining data on labor productivity for 2003–2014, show that labor productivity at Russian enterprises was significantly lower than in a number of European countries, including both developed and transition economies. They also report a declining rate of labor productivity growth throughout the period under review. Another observation is that the productivity gap between the most and least efficient enterprises widened during this period; moreover, this gap was larger in Russia than in other countries. Abramov et al. (2023), analyzing data on TFP of Russian enterprises for a later period, 2012–2020, also show that the average productivity growth rate was mostly negative. Furthermore, they find a growing productivity gap between large and small enterprises in most sectors. Kislitsyn and Orekhova (2019), analyzing micro-level productivity in the extractive and manufacturing industries for 2013–2017, show that TFP growth rates at small enterprises were significantly lower than at large and medium-sized enterprises.

A recent study by Kaukin and Zhemkova (2023), which employs the approach proposed by Hsieh and Klenow (2009) to assess resource allocation efficiency in Russian manufacturing, reveals a reduction in allocation efficiency across Russian manufacturing sectors from 2012 to 2018. Tsvetkova (2021), estimating stochastic frontiers on 2013–2018 data, shows that after 2014, Russian enterprises' technical efficiency either remained unchanged or declined. Moreover, the contribution of industries with decreasing technical efficiency to total output and employment in the analyzed dataset was over 50%.

Thus, studies using microdata for Russia show a downward trend in firms' average productivity between the global financial crisis and the atypical crisis caused by the COVID-19 pandemic. In addition, a number of studies highlight a widening productivity gap between large and small firms, as well as a decline in or stagnation of technical efficiency in most sectors of the economy.

Building on previous research, we aim to conduct a more rigorous study of productivity dynamics in the Russian economy using stochastic production func-

tions. Prior studies on developed countries, and to some extent on Russia, note growing productivity gaps within industries. Using SFA allows us to simultaneously assess firm-level productivity dynamics and the gap between the most efficient firms, which define the stochastic production possibility frontier, and other firms in a given industry.

3. Methodology and data

TFP growth can be measured using several approaches. Growth-accounting and index methods, such as the Solow residual and Törnqvist or Malmquist indices, use aggregate inputs and outputs but do not correct for measurement error and are best suited for sector-level analysis. Parametric and semi-parametric production function methods (e.g., GMM and the Olley–Pakes or Levinsohn–Petrin approaches) impose more structure, which makes them suitable for firm-level studies.

Within the class of frontier-based methodologies, SFA is distinguished by its capacity to accommodate noisy and unbalanced firm-level datasets, enabling the decomposition of TFP growth into frontier expansion (technological progress) and changes in technical efficiency, benchmarked against industry leaders. The main limitations of SFA include sensitivity to model choices and the need for parametric assumptions. In contrast, nonparametric methods, such as data envelopment analysis (DEA), avoid parametric assumptions but are sensitive to outliers and typically require balanced panels. DEA is more often used when researchers consider entities with multiple outputs that are difficult to convert into comparable value terms (e.g., schools, hospitals).

In estimates based on standard production functions, TFP growth is obtained as an unexplained residual, which may unintentionally capture factors such as measurement error. By contrast, stochastic production function estimates allow TFP to be decomposed into separate components, including technological progress and changes in inefficiency, which should, in principle, mitigate the impact of such undesirable elements. This advantage comes at the cost of a more heavily parameterized model, implying an inherent trade-off between model complexity and the influence of unexplained residual variation.

Which approach is more appropriate is ultimately context-dependent and may vary with the research objective, the characteristics of the sample, and the time period under study. In the present paper, the preference is for a stochastic specification because the empirical task requires the joint estimation of productivity growth and the distance to the production-possibility frontier, rather than constructing these measures by combining results from different methods.

In this study, SFA is employed to estimate TFP growth rates and the distance to the production-possibility frontier for each firm in the sample. Under SFA, the standard production function $Y = F(K, L, t)$ is modified to include a stochastic term that reflects inefficiency:

$$Y = F(K, L, t) \cdot e^{-u(t)}. \tag{1}$$

It denotes the fact that not all firms succeed in organizing production efficiently, with some operating below the production-possibility frontier determined by the most efficient firms.

The deterministic part of the production function is modeled as a translog function of three arguments — labor (L), capital (K), and time (t):

$$\ln Y_{it} = \alpha + \alpha_L \ln L_{it} + \alpha_K \ln K_{it} + \alpha_t t + \alpha_{LL}(\ln L_{it})^2 + \alpha_{KK}(\ln K_{it})^2 + \alpha_t t^2 + \\ + \alpha_{KL} \ln K_{it} \ln L_{it} + \alpha_{Kt} \ln K_{it} \cdot t + \alpha_{Lt} \ln L_{it} \cdot t - u_{it} + \varepsilon_{it}, \quad (2)$$

where ε_{it} is a standard i.i.d. error term and u_{it} is a nonnegative inefficiency component.

Following Battese and Coelli (1995), we model the inefficiency term u_{it} as a function of firm-specific variables and time:

$$u_{it} = e^{-\gamma(t-T)} u_i, \quad (3)$$

$$u_i \sim N^+(\mu, \sigma^2). \quad (4)$$

Under these assumptions, firm-level TFP growth can be decomposed into three components (see Kumbhakar and Lovell, 2003): the rate of technological progress (the shift in the production frontier between the two crises), the change in technical inefficiency (the change in the distance to the shifting frontier), and the returns-to-scale term.

Formally,

$$\Delta TFP = \Delta TP + \Delta TE + RTS, \quad (5)$$

$$\Delta TP = \frac{\partial \ln F(K, L, t)}{\partial t}, \quad (6)$$

$$\Delta TE = -\frac{\partial u_{it}}{\partial t}, \quad (7)$$

$$RTS = (v - 1)\left(\frac{\eta_K}{v} \frac{\Delta K}{K} + \frac{\eta_L}{v} \frac{\Delta L}{L} \right), \quad (8)$$

where $v = \eta_K + \eta_L$ denotes returns to scale; η_K and η_L are the output elasticities of capital and labor, respectively.

The implemented specification of the inefficiency term used herein assumes a constant trend in changes in inefficiency over the period under study. Blöechliger and Wildnerova (2020) show a gradual widening of the productivity gap from 2003 to 2014. Tsvetkova (2021), using data from 2013 to 2018, also finds an increase in the dispersion of inefficiency over time. Therefore, drawing on previous research, the constant rate of change in inefficiency embedded in the econometric model should not significantly distort the results. This study analyzes data for 2009–2015, with the initial year coinciding with the global financial crisis. In subsequent years, Russia did not experience major economic shocks, aside from the imposition of sanctions against a number of large enterprises in 2014. This context allows the imposition of sufficiently strict constraints on the parameters of the stochastic function without loss of generality.

The period from 2009 to 2015 was chosen for the productivity analysis for two main reasons. First, this timeframe allows a comparison of productivity dynamics between two crises — the global financial crisis of 2008–2009 and the atypical

crisis of 2020 — since studies of productivity trends highlight a significant slowdown in growth rates during these years across many countries. Second, obtaining an accurate estimate of the stochastic frontier production function requires a sufficiently stable sample of enterprises so that the frontier reflects changes in firm-level productivity rather than changes in sample composition.

From 2016 onward, the structure of enterprise databases in various Russian sources changed substantially as they began to include data on small and medium-sized enterprises (SMEs), which significantly affected measured productivity trends. Moreover, after 2014, a number of large sanctioned enterprises stopped disclosing their balance sheet information in open sources. In recent years, balance sheets for large and medium-sized enterprises have also started to include payroll fund data, enabling more accurate calculations of value added, but these figures are not comparable with the data available at the beginning of the study period. Consequently, it is not possible to extend the series to subsequent years using the same data construction methodology for SFA. Restricting the sample to 2009–2015 therefore ensures that it remains stable and that all variables of interest are calculated using a consistent methodology.

To estimate stochastic production functions, we use data from the RUSLANA database. Over the period under study, this database collected balance sheet information from large and medium-sized enterprises, allowing the calculation of each firm's value added, labor, and capital required to estimate TFP growth. At the same time, SMEs are excluded from the analysis because most of them lack the data required to calculate value added and information on the number of employees. The economic literature typically assumes that SMEs can drive innovation in an economy, but research on the Russian economy (e.g., Kislitsyn and Orekhova, 2019) suggests that small businesses generally exhibit lower productivity growth. Therefore, excluding SMEs from the analysis for Russia is unlikely to introduce a significant bias in estimates of the stochastic production-possibility frontier.

The sample includes data on the following nonfarm, nonfinancial sectors according to the NACE Rev. 1.1 classification:

- Section C. Mining and quarrying;
- Section D. Manufacturing;
- Section E. Electricity, gas, and water supply;
- Section G. Wholesale and retail trade; repair of motor vehicles, motorcycles, and personal and household goods;
- Section H. Hotels and restaurants;
- Section I. Transport, storage, and communications;
- Section K. Real estate, renting, and business activities;
- Section O. Other community, social, and personal services activities (subsections 92 "Recreational, cultural and sporting activities" and 93 "Other service activities").

Stochastic production functions are estimated separately for 274 industries, mainly at the three- or four-digit level according to the NACE Rev. 1.1 classification.[1] The number of firms by sector is presented in Table 1.

[1] See Supplementary materials 1 and 2 for a detailed list of industries and the results of stochastic production function estimates, respectively.

Table 1
Number of observations by sector, 2008–2015 (NACE Rev. 1.1).

Code	Sector	2008	2009	2010	2011	2012	2013	2014	2015	Total
C	Mining and quarrying	1,351	1,381	1,398	1,659	1,555	1,852	2,046	2,065	13,307
D	Manufacturing	23,063	24,539	24,672	28,147	25,064	30,252	33,434	33,459	222,630
E	Electricity, gas, and water supply	2,142	2,426	2,411	2,503	2,671	3,056	3,293	3,531	22,033
G	Wholesale and retail trade	54,267	62,450	62,946	72,571	57,997	71,238	76,549	74,116	532,134
H	Hotels and restaurants	3,720	4,573	4,651	5,511	5,505	7,334	7,860	7,436	46,590
I	Transport, storage, and communications	7,393	8,063	8,147	9,538	8,565	10,703	12,139	12,295	76,843
K	Real estate, renting, and business activities	21,484	22,760	21,905	23,640	19,524	22,672	27,887	31,507	191,379
O	Other community, social, and personal services activities	2,617	2,822	2,812	2,962	3,004	3,677	4,053	3,869	25,816
	Total	116,037	129,014	128,942	146,531	123,885	150,784	167,261	168,278	1,130,732

Note: 2008 observations are reported for completeness/initial conditions, while the estimation window is 2009–2015.
Source: Compiled by the author.

To estimate stochastic production functions, we use data on value added (Y), capital (K), and employment (L). The RUSLANA database does not contain firm-level wage-bill (payroll fund) data consistently over the entire observation period. Therefore, firm-level value added is constructed as:

Value Added of firm i over period t =
= Total Sales of firm i over period t –
– (Total Costs of firm i over period t –
– Average Wages in region k and industry j over period t ×
× Number of Employees at firm i over period t).

Rosstat collects data on average wages separately for each of the Russian regions in a fairly detailed breakdown by industry, and therefore, the indicator of labor costs based on the average wage in a region and data on the number of employees at an enterprise can be considered a good approximation of this type of costs.

Value added is deflated using sectoral producer price indices for sectors C, D, and E, and SNA deflators for the remaining sectors. Capital deflators are derived from Rosstat's sector-level data on nominal capital stocks and volume indices of capital stocks.

4. Results

4.1. Main trends in average TFP growth and its decomposition

TFP growth was estimated for each firm and decomposed into the rate of technological progress, the change in technical efficiency, and the returns-to-scale (RTS) term. Fig. 1 and Appendix A Table A1 present the average growth rates of TFP and its components. Fig. 1 shows a sizable rate of technological progress, which increased over the observation period — from about 3% to about 9% per year on average. At the same time, the average efficiency level steadily declined over the post-crisis period by about 12% per year. This implies that the production-possibility frontier shifted upward as the most efficient enterprises advanced, whereas a substantial

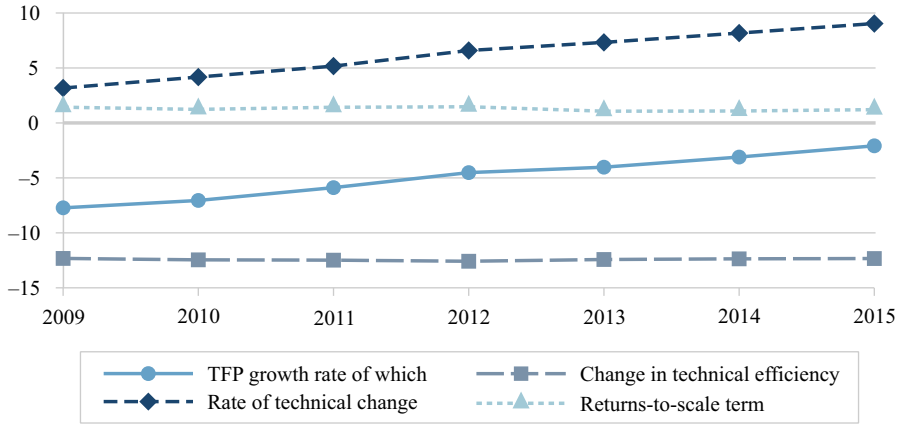

Fig. 1. Average TFP growth and its decomposition (%).

Source: Author's calculations.

proportion of firms failed to innovate; laggards did not succeed in catching up. Consequently, average TFP growth was negative throughout the post-crisis period. However, the decline slowed toward the end of the period. The contribution of the RTS term is close to zero and does not materially affect TFP growth.

The estimates for Russia are consistent with the results of Andrews et al. (2016), based on data for 24 OECD countries. They argue that the key aspect of the productivity slowdown lies less in slower productivity growth at the global frontier and more in the combination of rising labor productivity at the global frontier and a widening gap in labor productivity between leading and lagging firms. Similarly, Brandt et al. (2022) find declines in TFP growth after 2007 in Chinese data, although the downward trend in China was less pronounced than in advanced economies and was not widespread across all industrial sectors.

Overall, the simple average growth rate of TFP in the economy remained negative over the period under review, although the rate of decline slowed. In particular, the average rate of decline was –7.7% immediately following the global financial crisis, subsequently decelerating to –2.1% by 2015. The analysis of labor productivity dynamics for Russian enterprises by Blöechliger and Wildnerova (2020) shows similar dynamics, with labor productivity decreasing over a comparable period.

In terms of the value-added-weighted average growth rate of TFP, the slowdown in the decline was already noticeable in 2012–2013, when it decelerated to –1.2% and –1.1%, respectively, from –5.4% in 2009. In 2015, the TFP growth rate was already positive, reaching 1.6%. Comparison of the simple average TFP growth rate and the value-added-weighted average (see Fig. 2 and Appendix A Table A1) indicates that firms with high productivity growth increased their market shares in the post-crisis period.

Research on the Russian economy (Kislitsyn and Orekhova, 2019; Abramov et al., 2023) shows higher rates of productivity growth among large companies and often persistently negative growth rates among smaller ones. These results are consistent with our finding that less efficient companies shrink in size but remain in the market. Similar results for China and India are reported in the seminal work by Hsieh and Klenow (2009), who show that inefficient resource allocation among firms in these economies leads to efficiency losses and slower economic growth.

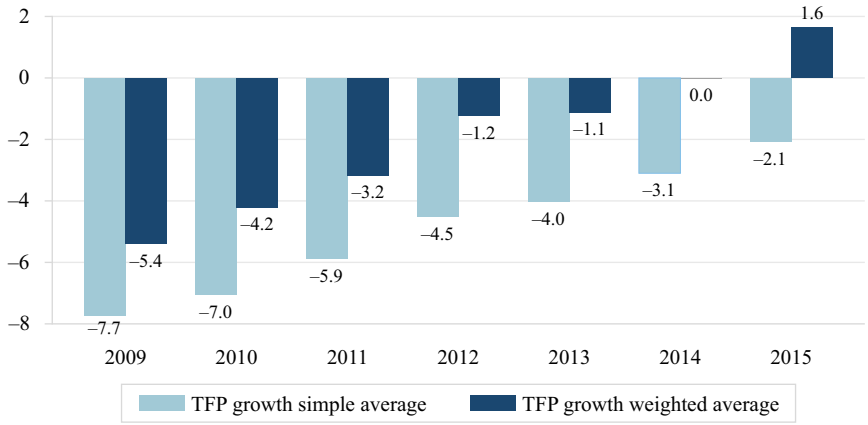

Fig. 2. TFP growth trends (%).

Source: Author's calculations.

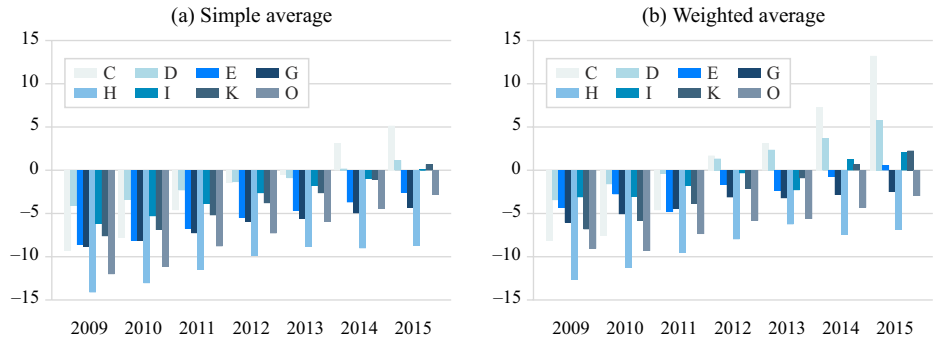

Fig. 3. TFP growth by sector (%).

Note: Sector C — Mining and quarrying; Sector D — Manufacturing; Sector E — Utilities; Sector G — Wholesale and retail trade; Sector H — Hotels and restaurants; Sector I — Transport and communications; Sector K — Real estate, renting and business activities; Sector O — Other community, social and personal services activities.
Source: Author's calculations.

TFP growth rates vary across industries (see Fig. 3 and Appendix A Tables A2 and A3). Mining and manufacturing exhibited positive value-added-weighted average growth rates starting in 2012; that is, the impact of the global financial crisis on these industries was not as strong and persistent as in services. Nevertheless, firms in different service sectors recovered differently. Thus, firms in transport and communications (Sector I) and business activities (Sector K) demonstrated positive dynamics at the end of the period. By contrast, sectors mostly oriented toward households — in particular retail, hotels and restaurants, and personal services (Sectors G, H, and O) — showed a decline in productivity over the entire observation period.

Comparison of simple averages with weighted averages by sector reveals the same pattern as for the economy as a whole: value-added-weighted average TFP growth rates are higher than simple averages in all sectors. However, TFP growth in mining and manufacturing was significantly positive from 2012 in terms of weighted averages and from 2014 in terms of simple averages, while household-focused service sectors did not reach positive values over the period under review even in terms of weighted averages.

The cumulative growth rates (see Fig. 4 and Appendix A Tables A4 and A5) show that all sectors experienced a sharp decline after the crisis. The decline then slowed, but to different degrees. The simple-average cumulative growth rates recover and turn positive by the end of the period only in mining and quarrying and, to a lesser extent, in manufacturing. It should be stressed that while the decline in mining and quarrying was more severe than in manufacturing, recovery was also faster. In transport and communications and in business activities, the decline during the crisis was comparable to that in manufacturing, followed by stagnation. The decline in other service sectors (trade, hotels and restaurants, and personal services) during the first years of the crisis was substantial and continued until 2015. Overall, none of the sectors restored the simple-average level of TFP to its 2008 level.

In part, these smooth dynamics are explained by the production-function specification, which imposes a constant rate of change in inefficiency. Because the contribution of this component to TFP growth is large, it mostly determines the trends described above.

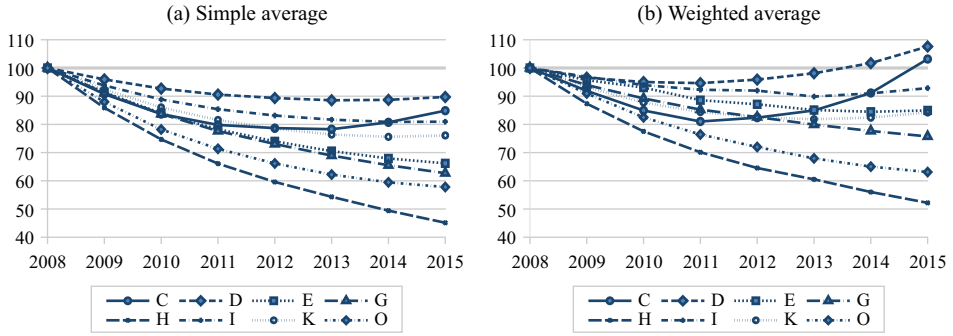

Fig. 4. Accumulated TFP growth by sector (index, 2008 = 100).

Note: Sector C — Mining and quarrying; Sector D — Manufacturing; Sector E — Utilities; Sector G — Wholesale and retail trade; Sector H — Hotels and restaurants; Sector I — Transport and communications; Sector K — Real estate, renting and business activities; Sector O — Other community, social and personal services activities.
Source: Author's calculations.

Fig. 4 also shows cumulative growth rates for value-added-weighted averages. These tend to be closer to indicators computed from aggregate data because they largely reflect the contribution of big market participants. According to these data, the decline in manufacturing was not severe and could be described as stagnation, with average TFP in this industry exceeding the 2008 level by the end of the period under review. By contrast, the decline in mining and quarrying was more severe, but recovery by the end of the period was also faster. In services, even the weighted-average indicators show either stagnation (transport and communications, business activities, utilities, and trade) or a decline (hotels and restaurants, personal services).

Overall, the immediate effect of the global financial crisis was quite strong in almost all sectors, except possibly manufacturing. However, the persistently negative growth rates from 2011 onward can hardly be explained solely by a protracted impact of the global financial crisis. Rather, the evidence points to a persistent slowdown in growth rates that became more evident in the post-crisis period. Similar results have been obtained for other countries. On the one hand, cross-country studies find that the immediate impact of the global financial crisis on productivity was strong; on the other hand, signs of a slowdown in productivity growth ("secular stagnation") were evident even before the crisis. Hence, the deceleration in productivity growth during this period cannot be attributed entirely to the crisis itself (Andrews et al., 2016; Cao and Mao, 2022; Cerdeiro and Ruane, 2024).

4.2. TFP growth by efficiency group

The economic literature (e.g., Syverson, 2011; Hsieh and Klenow, 2009; Decker et al., 2016) documents a trend toward increasing dispersion of productivity within narrowly defined industries. Bahar (2018) attributes rising dispersion to high growth rates among very productive firms and new firms starting from a low base, while firms in the middle of the distribution exhibit very moderate growth. Andrews et al. (2016), examining the period following the 2009 global financial crisis, identify a widening productivity gap between industry leaders and other firms. They argue that these dynamics contributed to slower aggregate productivity growth because the low performance of a large share of laggards offset the high growth achieved by leaders.

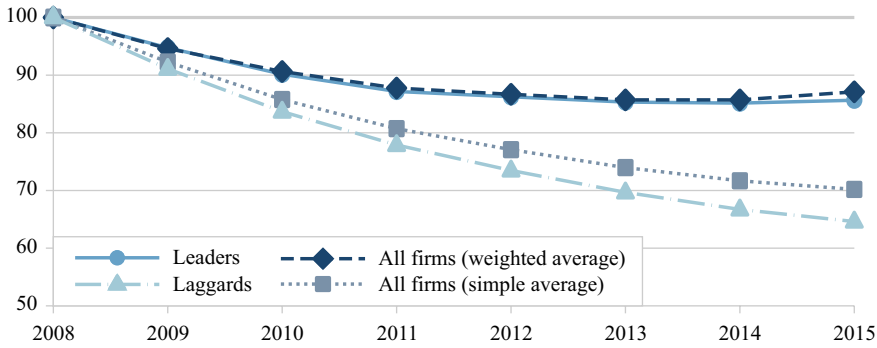

Fig. 5. Accumulated TFP growth by efficiency group (%).

Source: Author's calculations.

To examine productivity growth trends among technology leaders and laggards, we split the sample into two groups:

- *Leaders*: the top 10% of firms with the highest technical efficiency (i.e., closest to the frontier within an industry).
- *Laggards*: firms below the median of technical efficiency within an industry.

Leaders and laggards are identified separately in each of the 274 industries for which the production function is estimated. One advantage of SFA is a stable group of leaders. Because the production frontier is determined for the entire period by construction, the set of frontier firms is relatively stable, with about 90% of enterprises retaining their status throughout the period under review. The choice of 10% as the leader group follows Andrews et al. (2016), facilitating comparison of results for Russia with patterns observed in OECD countries.

As in Andrews et al. (2016), the estimates show that the gap between leaders and other enterprises widens over the period under review (see Fig. 5 and Appendix A Table A6). However, the underlying trends differ. In OECD countries, leaders substantially improve productivity, while lagging enterprises exhibit near-zero growth; moreover, the impact of the global financial crisis on TFP and labor productivity is relatively short-lived. In Russia, the crisis is associated with a decline in productivity growth among both leaders and laggards, but the magnitude of the decline differs between the two groups.

The results suggest that the crisis imposed a heavier burden on laggards. Less efficient firms experienced a pronounced productivity decline during the first three years after the crisis, and TFP continued to fall in this group through the end of the period, although the decline gradually slowed. Leaders also show a decline in productivity in 2009–2010, but the contraction is less pronounced; from 2011 onward, productivity among leaders is broadly stable.

Andrews et al. (2016) also report TFP growth patterns in services and manufacturing. In their data, frontier firms in services maintained high TFP growth even after the crisis, whereas leaders in manufacturing experienced stagnation around pre-crisis levels after the crisis period ended. Lagging enterprises in both services and manufacturing showed near-zero productivity growth. In Russia, leaders exhibit different dynamics. In manufacturing, the post-crisis pattern among leaders is closer to stagnation, but at a lower level than at the beginning of the crisis. By contrast, in services, TFP declined even among leaders. Lagging

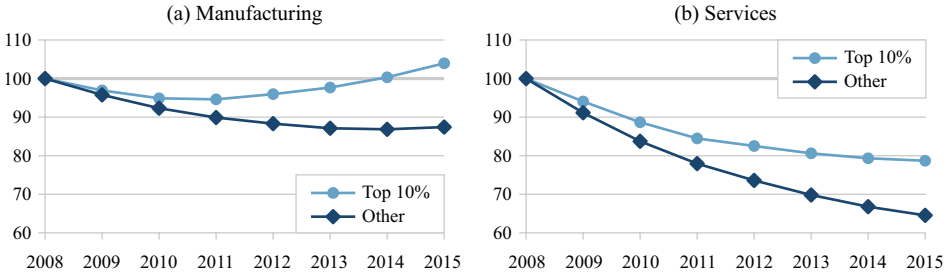

Fig. 6. Accumulated TFP growth by efficiency group in manufacturing and services (%).

Source: Author's calculations.

enterprises, on average, experienced a decline in TFP after the crisis, and the rate of decline in services was higher (see Fig. 6 and Appendix A Table A7).

These results likely reflect cross-country differences in the composition of frontier firms in services. In OECD countries, such firms include a higher share of very large enterprises related to information and communication technologies (ICT), which are global leaders and therefore shift the services frontier. In Russia, the share of large enterprises in services is smaller, and the sector is largely represented by (relative to global benchmarks) smaller firms in trade, where innovation adoption is traditionally more limited.

Similar results are reported by Vujanović (2021) for Montenegro. Using data for 2010–2019, the author finds a clear upward trend in technical efficiency in manufacturing, whereas firms in services show limited progress in innovation.

It is also worth noting that traditional services (trade, hotels and restaurants, personal services) are generally characterized by lower innovation intensity. For example, the sharp drop in productivity during the transition from a planned to a market economy is often explained by the rising share of household-oriented services, which were underdeveloped under central planning (Voskoboynikov, 2017). At the same time, services also include sectors with high innovation potential (e.g., ICT).

The trends in Figs. 5 and 6 suggest that diffusion of new technologies from national leaders to less efficient enterprises is very limited in Russia, and that the productivity gap between leaders and laggards widened over the post-crisis period mainly due to declining productivity among less efficient firms. The most efficient enterprises gradually increased their market shares, but low-performing enterprises did not exit the market. Consequently, scarce resources remained locked in inefficient production.

Syverson (2011), Hsieh and Klenow (2009), and Andrews et al. (2016) argue that the productivity gap persists in part because inefficient firms do not exit markets for a long time. This raises the question of how inefficient enterprises manage to remain in the market. In discussions of secular stagnation between the two global crises, a common explanation is exceptionally low (near-zero) interest rates in advanced economies. Cheap credit allowed inefficient enterprises to refinance debts for years. By contrast, Russia did not experience a prolonged period of near-zero interest rates, and external financing has typically been expensive for enterprises. Therefore, the persistence of the productivity gap between the most and least efficient enterprises in Russia is likely driven by other factors.

This opens scope for further, more in-depth research on productivity trends, especially in more recent years, because such factors may materially affect

growth across industries during subsequent shocks. Related research (Bessonova and Tsvetkova, 2022) suggests that inefficient firms are concentrated in less developed regions. Bessonova (2023) discusses support for inefficient firms through government procurement, especially in less developed regions.

4.3. TFP growth in industries by involvement in ICT production and use

Finally, we split the sample into three groups depending on firms' involvement in ICT production and use. ICT producers exhibit the highest TFP growth rates: firms in this group were not adversely affected by the global financial crisis and increased their annual growth rates over 2009–2015. By contrast, ICT users experienced a slowdown in TFP growth, while non-ICT-intensive sectors show a relatively moderate catch-up trend during the post-crisis period (see Fig. 7 and Appendix A Tables A8 and A9).

The reasons for slower diffusion of new knowledge and technologies from global and national leaders to lagging enterprises may vary across economies depending on their level of development and across industries. The OECD survey (Andrews et al., 2015) identifies several mechanisms that impede technology diffusion across firms:

- inadequate involvement of national leaders in global value chains;
- low mobility of skilled labor; and
- low rates of entry of new enterprises into an industry and exit of inefficient enterprises from an industry.

In the Russian economy, these three mechanisms may substantially slow diffusion of technological progress from efficient to lagging enterprises.

First, the involvement of Russian firms in international trade, in both manufacturing and services, is limited. As a result, diffusion of new technologies and organizational innovations from global leaders is confined to a relatively small part of the economy (Volchkova, 2017). Moreover, foreign policy factors that began to affect Russian firms' foreign-trade behavior during the period under consideration also reduced their ability to adopt new technologies from international companies operating in global markets.

Second, a distinctive feature of the Russian labor market is underinvestment in human capital. While the average level of workforce skills in Russia is relatively high, participation in on-the-job training programs is insufficient (Denisova et al.,

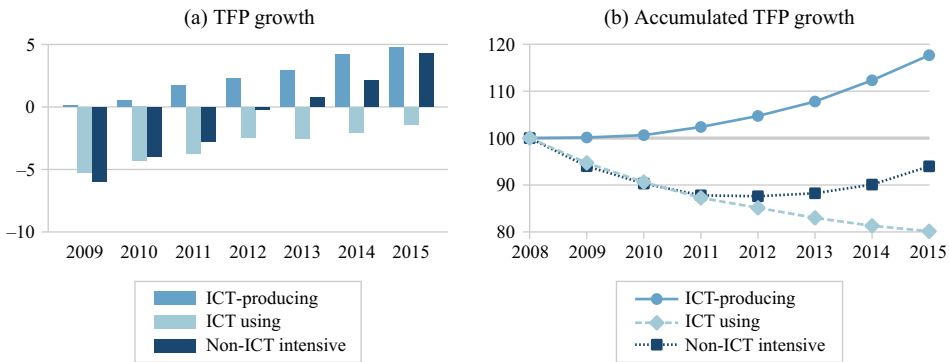

Fig. 7. TFP growth by ICT group (weighted average, %).

Source: Author's calculations.

2011). Employers lack effective mechanisms to limit personnel turnover and are therefore not incentivized to invest in human capital. Consequently, the scale of on-the-job training is inadequate, limiting diffusion of new technologies and, especially, organizational innovations that rely on tacit knowledge.

Third, our analysis indirectly suggests that in most sectors a sizable share of inefficient enterprises remains in the market for a long time, slowing productivity growth and locking production factors in small, inefficient firms. This persistence may also reflect limited competition in product markets and underdeveloped bankruptcy mechanisms.

5. Conclusion

In the aftermath of the 2008–2009 global financial crisis, the economic literature has widely discussed the problem of slower economic growth associated with declining productivity. Several studies (e.g., Andrews et al., 2016) attribute the slowdown in aggregate productivity growth to a widening gap between industry leaders and laggards. Research on resource allocation inefficiencies (Hsieh and Klenow, 2009) also points to constraints on growth in developing economies — namely China and India — driven by institutional factors that limit the expansion of more efficient firms.

Russia has also experienced a decline in productivity since the 2008–2009 crisis, as documented in both aggregate data (Voskoboynikov, 2017) and microdata (Abramov et al., 2023). This study provides additional evidence on declining productivity among Russian firms in 2009–2015 by examining productivity trends of leaders within specific industries relative to laggards. We estimate firm-level TFP growth and decompose it into three components: the rate of technological progress, the change in technical efficiency, and the returns-to-scale term. The results indicate significant technological progress; however, the gap between frontier firms and laggards widened over the entire period under consideration. The latter failed to catch up, and the productivity gap continued to increase during the period between the two global crises — the 2008–2009 financial crisis and the atypical crisis caused by the COVID-19 pandemic. Consequently, most sectors experienced negative average TFP growth in 2009–2015.

Over 2009–2015, the value-added-weighted average growth rate of TFP largely reflected the productivity dynamics of the most efficient enterprises, suggesting that these firms increased their market shares in domestic markets. At the same time, a sizable share of low-performing firms in the Russian economy did not control a significant market share but also did not exit the market, continuing to use production factors inefficiently.

To accelerate TFP growth, policy should focus on creating conditions that allow inefficient firms to exit more quickly or be restructured. This can be achieved by simplifying bankruptcy procedures, redirecting government support from distressed to expanding enterprises, and introducing programs to retrain or reemploy workers leaving inefficient firms. Strengthening competition also requires reducing administrative barriers to entry and barriers that constrain the growth of efficient enterprises. Because cost reduction is an important channel for improving performance and productivity, the government can contribute by eliminating unreasonable regulatory and administrative obstacles that impose high compliance costs on Russian firms.

A limitation of this study is its focus on 2009–2015, which does not cover more recent shocks such as the COVID-19 pandemic, heightened geopolitical tensions, or various sanctions affecting Russian enterprises. Methodological constraints — including comparability of the enterprise sample across years, consistent construction of key variables, and model parameterization — make it difficult to extend the analysis to later years using the same approach. Future research could use more recent data to assess whether the observed productivity patterns persisted under these new challenges.

Further investigation is needed to determine whether the productivity gap has continued to widen in recent years. The mechanisms behind this gap and the persistence of inefficient firms may materially affect growth across industries, especially amid ongoing shocks. Aggregate data indicate heightened volatility in labor productivity since 2015, linked to atypical events such as the pandemic and geopolitical disruptions. It is therefore important to examine how new factors — such as pandemic-era government support or sanctions — have affected productivity among leading firms and other enterprises.

Finally, research by Blöechliger and Wildnerova (2020) and Bessonova and Tsvetkova (2022) highlights the role of regional differences in productivity among Russian enterprises. A promising direction for future work is to investigate regional determinants of firms' innovation decisions and productivity dynamics, particularly in the current economic environment.

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Appendix A. Total factor productivity growth by year, sector, efficiency group, and ICT group

Table A1
TFP growth by component, all industries (%).

Year	TFP growth (simple average)	Average rate of technical change	Average change in technical efficiency	Average returns-to-scale term	TFP growth (value-added-weighted average)
2009	–7.72	3.17	–12.32	1.43	–5.39
2010	–7.05	4.17	–12.45	1.23	–4.20
2011	–5.89	5.17	–12.48	1.42	–3.17
2012	–4.52	6.59	–12.58	1.47	–1.23
2013	–4.02	7.33	–12.42	1.07	–1.12
2014	–3.10	8.17	–12.36	1.08	–0.01
2015	–2.08	9.04	–12.33	1.21	1.64

Source: Author's calculations.

Table A2
TFP growth by sector, simple average (%).

Code	Sector	2009	2010	2011	2012	2013	2014	2015
C	Mining and quarrying	–9.26	–7.80	–4.59	–1.42	–0.50	3.10	5.13
D	Manufacturing	–4.05	–3.38	–2.30	–1.35	–0.89	0.17	1.14
E	Utilities	–8.62	–8.13	–6.75	–5.49	–4.67	–3.69	–2.55
G	Wholesale and retail trade	–8.84	–8.15	–7.26	–5.93	–5.62	–4.95	–4.29
H	Hotels and restaurants	–14.11	–13.04	–11.49	–9.84	–8.84	–9.01	–8.70
I	Transport and communications	–6.20	–5.30	–3.88	–2.63	–1.76	–0.96	0.08
K	Real estate, renting and business activities	–7.61	–6.89	–5.19	–3.79	–2.63	–1.07	0.66
O	Other community, social and personal services activities	–12.00	–11.12	–8.78	–7.27	–5.96	–4.43	–2.79

Source: Author's calculations.

Table A3
TFP growth by sector, value-added-weighted average (%).

Code	Sector	2009	2010	2011	2012	2013	2014	2015
C	Mining and quarrying	–8.10	–7.57	–4.60	1.67	3.10	7.29	13.21
D	Manufacturing	–3.44	–1.60	–0.41	1.32	2.35	3.66	5.79
E	Utilities	–4.30	–2.76	–4.81	–1.64	–2.33	–0.74	0.57
G	Wholesale and retail trade	–6.03	–5.06	–4.44	–3.11	–3.22	–2.83	–2.50
H	Hotels and restaurants	–12.65	–11.24	–9.54	–7.96	–6.24	–7.42	–6.85
I	Transport and communications	–3.10	–3.05	–1.77	–0.33	–2.29	1.26	2.04
K	Real estate, renting and business activities	–6.81	–5.83	–3.85	–2.13	–0.90	0.68	2.25
O	Other community, social and personal services activities	–9.04	–9.31	–7.36	–5.80	–5.61	–4.30	–2.96

Source: Author's calculations.

Table A4
Accumulated TFP growth by sector, simple average (index, 2008 = 100).

Code	Sector	2008	2009	2010	2011	2012	2013	2014	2015
C	Mining and quarrying	100	90.7	83.7	79.8	78.7	78.3	80.7	84.9
D	Manufacturing	100	96.0	92.7	90.6	89.4	88.6	88.7	89.7
E	Utilities	100	91.4	84.0	78.3	74.0	70.5	67.9	66.2
G	Wholesale and retail trade	100	91.2	83.7	77.7	73.1	68.9	65.5	62.7
H	Hotels and restaurants	100	85.9	74.7	66.1	59.6	54.3	49.4	45.1
I	Transport and communications	100	93.8	88.8	85.4	83.1	81.7	80.9	81.0
K	Real estate, renting and business activities	100	92.4	86.0	81.6	78.5	76.4	75.6	76.1
O	Other community, social and personal services activities	100	88.0	78.2	71.3	66.2	62.2	59.5	57.8

Source: Author's calculations.

Table A5
Accumulated TFP growth by sector, value-added-weighted average (index, 2008 = 100).

Code	Sector	2008	2009	2010	2011	2012	2013	2014	2015
C	Mining and quarrying	100	91.9	84.9	81.0	82.4	84.9	91.1	103.2
D	Manufacturing	100	96.6	95.0	94.6	95.9	98.1	101.7	107.6
E	Utilities	100	95.7	93.1	88.6	87.1	85.1	84.5	85.0
G	Wholesale and retail trade	100	94.0	89.2	85.3	82.6	79.9	77.7	75.7
H	Hotels and restaurants	100	87.4	77.5	70.1	64.6	60.5	56.0	52.2
I	Transport and communications	100	96.9	93.9	92.3	92.0	89.9	91.0	92.9
K	Real estate, renting and business activities	100	93.2	87.8	84.4	82.6	81.8	82.4	84.2
O	Other community, social and personal services activities	100	91.0	82.5	76.4	72.0	67.9	65.0	63.1

Source: Author's calculations.

Table A6
Accumulated TFP growth by efficiency group (index, 2008 = 100).

Year	All firms (simple average)	All firms (value-added-weighted average)	Leaders (simple average)	Laggards (simple average)
2008	100.0	100.0	100.0	100.0
2009	92.3	94.6	94.8	91.1
2010	85.8	90.6	90.2	83.7
2011	80.7	87.8	87.2	77.9
2012	77.1	86.7	86.3	73.5
2013	74.0	85.7	85.3	69.7
2014	71.7	85.7	85.2	66.7
2015	70.2	87.1	85.7	64.6

Source: Author's calculations.

Table A7
Accumulated TFP growth by efficiency group in manufacturing and services (index, 2008 = 100).

Year	Manufacturing leaders (simple average)	Manufacturing laggards (simple average)	Services leaders (simple average)	Services laggards (simple average)
2008	100.0	100.0	100.0	100.0
2009	96.9	95.8	94.1	91.1
2010	94.9	92.3	88.7	83.7
2011	94.6	89.9	84.5	78.0
2012	96.0	88.3	82.5	73.6
2013	97.7	87.1	80.6	69.8
2014	100.3	86.9	79.3	66.8
2015	104.0	87.4	78.7	64.5

Source: Author's calculations.

Table A8
TFP growth by ICT group, value-added-weighted average (%).

Year	ICT-producing	ICT-using	Non-ICT intensive
2009	0.13	–5.28	–5.98
2010	0.49	–4.32	–3.94
2011	1.73	–3.72	–2.78
2012	2.29	–2.43	–0.22
2013	2.94	–2.51	0.72
2014	4.19	–2.03	2.10
2015	4.76	–1.44	4.32

Source: Author's calculations.

Table A9
Accumulated TFP growth by ICT groups, value-added-weighted average (index, 2008 = 100).

Year	ICT-producing	ICT-using	Non-ICT intensive
2008	100.0	100.0	100.0
2009	100.1	94.7	94.0
2010	100.6	90.6	90.3
2011	102.4	87.3	87.8
2012	104.7	85.1	87.6
2013	107.8	83.0	88.2
2014	112.3	81.3	90.1
2015	117.7	80.1	94.0

Source: Author's calculations.

Supplementary material 1

List of industries

Author: Evguenia V. Bessonova

Data type: Text

Explanation note: Detailed list of industries codes and description according to the NACE Rev. 1.1 classification.

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Link: https://doi.org/10.32609/j.ruje.12.169885.suppl1

Supplementary material 2

Stochastic production functions estimates

Author: Evguenia V. Bessonova

Data type: Text

Explanation note: Tables providing estimates of the stochastic production function regression coefficients for individual industries.

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