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DO PRODUCTIVITY LAGGARDS EVER CATCH UP WITH LEADERS?†

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The paper focuses on trends in the convergence of labor and multifactor productivity in Russia. Using firm-level data for the period 2011–2016, we show that firms with low-productivity grow faster than those with high-productivity. This result is, however, mostly driven by new entrants. The catch-up momentum fades after the first few years of a firm's life, so it is not capable of closing the gap between the most and least productive firms in the Russian economy. We show that the gap widened over the period 2011–2016, suggesting major divergence in productivity levels of Russian firms. We also use stochastic frontier analysis to verify the divergence within narrowly defined industries. Our estimates confirm divergence in most industries.

JEL Codes: D24, E22, O47

Keywords: productivity gap, β-convergence, σ-convergence, stochastic frontier analysis, Russia

1. Introduction

A large number of studies examining productivity dynamics in various countries provide evidence of a significant slowdown in productivity growth after the 2008 crisis. In recent years, advanced economies have experienced slower growth of both labor and multifactor productivity (MFP) (Syverson, 2017, for the US; Goodridge *et al.*, 2018, for the UK; Ollivaud *et al.*, 2016, for OECD countries; Bergeaud *et al.*, 2016, for advanced economies). These trends are observed on both aggregate and micro-level data. In fact, Cette *et al.* (2018), using macro- and microeconomic data for France, found downward structural breaks in productivity levels even several years before the crisis.

Annual changes in Russia's productivity growth rates are similar to the worldwide trends. Official statistics indicate that since 2009 labor productivity growth rates at an aggregate level have been significantly lower than in the earlier years of this century, which saw rapid growth (Timmer and Voskoboynikov, 2014) (see Figure 1). Negative rates of growth of aggregate productivity in Russia in 2015 and 2016 give particular cause for concern.

†*Note*: The views expressed in this paper are solely those of the authors and do not necessarily reflect the official position of the Bank of Russia. The Bank of Russia assumes no responsibility for the contents of the paper.

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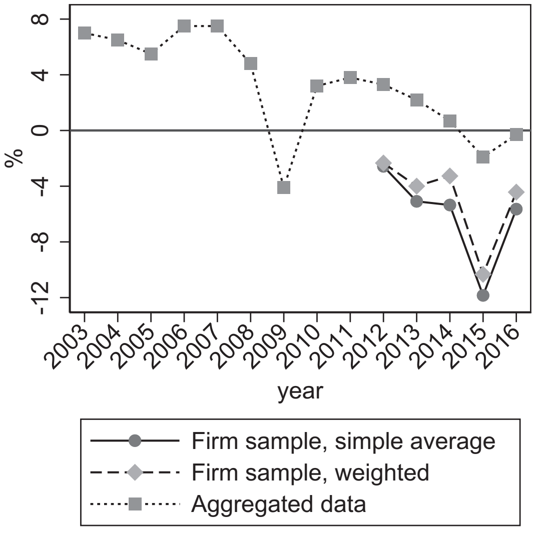

Figure 1. Labor Productivity Growth in Russia

Figure 1 also shows our estimates of labor productivity growth in recent years based on micro-level data.[1] Our estimations and aggregate labor productivity growth have similar trends. However, both simple and weighted averages of firms' productivity growth rates[2] are lower than the aggregated indicator. This suggests high heterogeneity of Russian firms in terms of productivity growth and size. The gap between aggregated productivity growth and sample estimations reflects the fact that there is huge number of small firms with relatively low productivity growth, while the small group of large and more efficient firms make a sizeable contribution to the aggregated indicator.

In recent literature, there is no generally accepted explanation for the causes of slowdown in productivity growth. The availability of firm-level data makes it possible to study this question at the micro level and to analyze the evolution of productivity distribution as well as changes in aggregate indicators.

A large body of literature shows heterogeneous productivity levels even in narrowly defined industries (for example, Hsieh and Klenow, 2009). This suggests that aggregate productivity growth depends not only on firms that operate at the productivity frontier, but also on a mass of non-frontier firms. While the productivity frontier is pushed forward by technological progress, the performance of laggards is also determined by the gap to the frontier. As Akcigit and Ates (2019) point out, knowledge diffusion between the frontier and the rest makes laggard firms more

[1]The first estimate is the unweighted mean of growth rates of firms' labor productivity in the sample. The second estimate is weighted productivity growth calculated as the difference between weighted average growth of value-added and the weighted growth rate of average employment.

[2]In line with Decker *et al*. (2017) and Foster *et al*. (2018) we find that weighted average productivity growth is higher than the simple unweighted mean since the correlation between size and labor productivity growth is positive. Popova (2019) shows similar results for correlation between output growth rates and firm size in Russia.

receptive to technological progress. So knowledge diffusion reduces dispersion of productivity levels, and makes industry more homogeneous.

Andrews *et al*. (2016) and Cette *et al*. (2018) show that the gap between frontier and laggard firms increases, because the frontier firms increase their productivity, while laggards drag aggregate productivity down. Decker *et al*. (2017) also point out that the dispersion of productivity levels within industries has increased in recent years. Akcigit and Ates (2019) argue that the reason for increasing heterogeneity of productivity is the reduction of knowledge diffusion.

However, another large body of literature analyzes convergence from a different perspective. Several papers document that low-productivity firms grow faster than high-productivity firms (see Chevalier *et al*., 2012; Brown *et al*., 2016; Bournakis and Mallick, 2018; Gemmell *et al*., 2018). These papers show positive correlation between the initial gap to the technological frontier and productivity growth, which implies catch-up to the frontier.

This conclusion is consistent with economic intuition for a number of reasons. Firstly, growth rates are affected by the low-base effect. Given the same absolute change, the lower the initial productivity level, the higher the growth rates. Secondly, observational errors also result in positive correlation between the initial productivity level and its rates of growth. If a firm presents annual financial reporting that shows productivity lower than its true value, then this firm will tend to report better performance in the next year (the productivity growth rates reported in the next year will reflect productivity improvements for two years instead of one). Thirdly, productivity laggards exit the market more often than efficient firms (Linarello and Petrella, 2017), but the mean growth rate among laggards does not account for market exits and for new low-productivity firms entering the market. It is therefore skewed towards surviving laggards with better performance that those, which exit.

The two strands in the literature might seem contradictory at first sight. The first body of papers claims divergence, while the other argues for convergence. The strands have hardly ever been linked, but some authors have noted that catch-up is consistent with persistent heterogeneity within narrowly defined industries (Griffith *et al*., 2009; Berlingieri *et al*., 2020). Several papers document positive correlation between initial gap to the frontier and productivity growth and simultaneous increase of the gap between leaders and laggards (Andrews *et al*., 2016; Cette *et al*., 2018). As Young *et al*. (2008) point out, catching up is not always accompanied by decrease of dispersion.

In the present paper we combine different approaches to convergence analysis and bring together the two strands in the literature. We study both catch-up and the dispersion. Using Russian micro-level data we analyze how these approaches to convergence analysis relate to each other. In particular, we test what catch-up to the frontier means in terms of dispersion. We show explicitly that the results obtained using the two approaches, which appear contradictory at first sight, may in fact coexist.

In line with the literature, we find that productivity growth rates in a sample of Russian firms are positively correlated with the initial productivity gap to the frontier. We show that this result is robust for different specifications and holds in all sectors and all years. We also consider the literature on the labor market (Haltiwanger *et al*., 2013) and firm life-cycle (Akcigit *et al*., 2021) and find that the main driver for fast growth by laggards is the group of new firms entering the market. Their productivity is lower than that of incumbents and they catch up with the older firms in the first years of their life.

However, after a few years, the catch-up momentum of the new entrants subsides. Their productivity growth rate slows down far short of the productivity frontier, as they draw equal with the productivity levels of incumbents (Bahar, 2018). So the catch-up momentum of young firms with low productivity is extinguished before they reach the frontier, and the gap between incumbents and the frontier remains wide.

We show how the productivity gap is persistent because the probability of transition from the lower to the higher quartile of the productivity distribution is small. We also show that the gap is much wider in the Russian economy than in OECD countries. In line with Andrews *et al*. (2016) and Cette *et al*. (2018), we find that the dispersion of productivity levels is increasing, indicating divergence from the frontier.

To check this result, we apply stochastic frontier models to firm-level data. We assume that firms may operate at a suboptimal level. We use two specifications for the evolution of inefficiency (i.e. distance to the frontier) over time. The first specification is relatively rigid, describing inefficiency trends with only one parameter, smoothing all fluctuations during the sample period. The second specification is more flexible, as it allows inefficiency to fluctuate from year to year. Our results indicate that technical efficiency decreases over the sample period in most industries under both specifications. This implies that the distance to the frontier (in other words, the gap between leaders and laggards) increases, confirming that rapid growth of the least productive firms does not lead to convergence of productivity levels.

We compare industries with and without divergence according to our first specification. We show that the absence of divergence in our sample is not the result of active knowledge diffusion from leaders to laggards, when all firms are stimulated by technological progress to grow fast. On the contrary, absence of divergence means that productivity of all firms, including productivity leaders, stagnates or even declines. We suggest two possible explanations. Firstly, if the performance of productivity leaders is good enough, it is more difficult to catch up with them, which discourage laggards from attempting to improve their efficiency. Secondly, slow growth at the frontier could indicate the presence of institutional barriers or unfavorable economic conditions for all companies. An industry that is experiencing difficulties becomes more homogeneous because all of its firms are handicapped.

The remainder of the paper is organized as follows. Section 2 summarizes findings in the related literature. Section 3 describes the data on Russian firms. In Section 4 we analyze productivity convergence using two approaches to measurement of convergence: correlation between the initial level of productivity and its growth (β-convergence); and dispersion analysis (σ-convergence). Section 5 uses stochastic frontier analysis to provide a robustness check for the key conclusion that the gap between leaders and laggards increases. Section 6 concludes.

2. Related Literature

In the literature convergence analysis was initially applied to cross-country studies. Research on a macro level has produced ambiguous results (Abreu *et al.*, 2005). On the one hand, catch-up by developing economies is driven mainly by technology transfers and capital deepening thanks to greater involvement in international trade and global value chains. Cross-country studies show a rise in living standards in rapidly growing developing economies (see Crafts and O'Rourke, 2014, for a detailed overview of historical trends in convergence). On the other hand, recent empirical studies do not confirm that there has been convergence between advanced economies since the beginning of the 21st century. For example, Bergeaud *et al.* (2016) find that convergence of developed economies on a macro level was observed for only a short period, with signs of divergence emerging after the 2008 crisis.

Other research devoted to growth and the convergence process emphasizes institutional frictions which prevent the adoption of new technologies in less developed economies (Acemoglu *et al.*, 2001). In this strand of literature, technical change is regarded as an endogenous factor, and its effects on leading and developing economies could differ depending on the adaptation capacity of these economies. Recent empirical studies stress special features of the process of technology transfer in the third wave of the technological revolution, which slow the diffusion of new technologies to economic agents below the technology frontier (Brynjolfsson and McAfee, 2012; Fernald, 2014; Gordon, 2015). Inklaar and Diewert (2016) using detailed industry-level data for 38 countries between 1995 and 2011 find that, on the one hand, decreasing dispersion of national productivity levels is observed during the period, but on the other hand, convergence to the average level of productivity is accompanied by an increasing gap between the average level of productivity and productivity at the frontier.

Empirical studies relying on micro-level data show that heterogeneity exists not only between countries with different levels of economic development but also within one narrowly defined industry in a particular country (see Syverson, 2011, for a review of research into productivity dynamics). In an analysis that uses firm-level data, the authors find that differences in productivity levels within one industry persist. In his review, Syverson (2011) formulates a simple theoretical model which predicts sustainable heterogeneity in productivity levels in a competitive environment due to different reactions of firms to exogenous shocks.

However, heterogeneity among firms does not necessarily have an adverse effect on aggregate productivity growth. Recent studies based on micro data show that an aggregate productivity slowdown arises from increasing dispersion between leaders and laggards within the same industry. Andrews *et al.* (2016) find that OECD countries are experiencing a widening gap between leaders and laggards, while the production frontier is still moving forward (at least in services). This suggests that decline of aggregate productivity is not due to a slowdown in technical progress but to increasing heterogeneity of firms within industries. Baily and Montalbano (2016) explain the phenomenon by weakening of the dynamic adjustments that have traditionally fueled productivity improvement.

An alternative body of literature explains substantial variation in productivity by resource misallocation. These papers provide an explanation for high productivity dispersion within narrowly defined industries. For example, as Hsieh and Klenow (2009) show, aggregate productivity in India and China could improve substantially if the reallocation of resources among companies in these countries changed productivity distribution in such a way as to make it similar to that in the U.S.

In the model of Hsieh and Klenow (2009), misallocation stems from two types of distortions, which prevent firms from expanding. The first type is scale distortions, whereby productive firms that try to expand face barriers such as size-dependent policy (Guner *et al.*, 2008). Examples of such policies are tax exemptions or direct subsidies to small companies. The second type of distortion leading to misallocation relates to capital. As Midrigan and Xu (2014) and Gopinath *et al.* (2017) point out, borrowing constraints may prevent productive firms from investing and from accumulating capital.

Bartelsman *et al.* (2013) argue that scale distortions prevent firms not only from expanding but also from entering the market. Midrigan and Xu (2014) add that borrowing constraints prevent firms from adopting technology and changing their production mode from labor-intensive to technology-intensive.

In addition to scale and capital distortions, Decker *et al.* (2018) suggest that resource misallocation arises from decreasing responsiveness of employment growth to productivity. In other words, they find that U.S. manufacturing firms hire less in response to high productivity (or fire less in response to low productivity).

The frictions described in this literature influence firms which do not grow although they are productive, but are they also relevant to firms which do not exit despite their low productivity. For example, Akcigit *et al.* (2021) compare the life cycle of firms in the U.S. and India. In the U.S., if firms are productive they take over resources from less productive firms and grow, while unproductive firms exit the market. Alon *et al.* (2018) confirm that productivity growth among young U.S. firms is driven by selection and allocation from quickly-exiting non-productive firms to expanding high-productivity firms. By contrast, in India productive firms face barriers that stop them growing and force them to stay small. Unproductive firms are not weeded out. As a consequence, there is a shortage of successful and productive companies in India, and the gap between leaders and laggards remains wide.

Andrews *et al.* (2016), as well as Akcigit and Ates (2019), suggest that slow technology diffusion may be among the forms of resource misallocation, since it denies firms access to tacit knowledge and opportunities to grow. In other words, as Midrigan and Xu (2014) point out with regard to borrowing constraints, the costs of moving from an economy based on production to an economy based on ideas is higher for laggard firms.

Andrews *et al.* (2016) find that the widening productivity gap goes along with a negative correlation between productivity growth and its initial level. This result is confirmed by the bulk of the literature (Griffith *et al.*, 2009; Chevalier *et al.*, 2012; Brown *et al.*, 2016; Bournakis and Mallick, 2018; Gemmell *et al.*, 2018). Andrews *et al.* (2016) suggest that this correlation has been weakening since 1997. They offer the following explanation: laggards catch up with leaders but it takes longer now; in other words, convergence slows down. Chevalier *et al*. (2012) claim that the speed of convergence among French firms declines due mainly to the high productivity growth rates of firms at the technology frontier. They explain this by greater impact of information technology and globalization on the most efficient companies. Bahar (2018) found a U-shape convergence curve with the highest MFP growth rates at the higher and lower bounds of the initial productivity distribution while the growth rates of firms in the middle of the distribution are significantly slower. He argues that this pattern is driven by firms in knowledge-intensive industries, possibly explained by stronger impediments to knowledge diffusion in these sectors. This problem is similar to the "middle-income trap" when middle-income countries, such as some Asian and Latin American emerging markets, experience a sudden deceleration of growth (Park and Mercado, 2018).

Other studies also show that high productivity growth at the lower bounds of the initial productivity distribution may be explained by the age structure of the productivity distribution. Haltiwanger *et al*. (2016) argue that startups and surviving young businesses are critical for job creation and contribute disproportionately to net growth in the U.S. Since new firms usually have low-productivity, their contribution is seen at the lower bounds of the productivity distribution. However, Ayyagari *et al*. (2011) show that the contribution of young firms (0–2 years) to total employment in developing economies is very small (the mean is 6.75 percent), while old firms (10+ years) contribute the most. According to their estimations, in developing economies, small and old firms account for the greater share of both employment and job creation. So developing economies are based on firms that are old but are not growing and not increasing their market share. Moreover, Ayyagari *et al*. (2011) show that in countries where the contribution of small firms is larger, GDP per capita is lower, reflecting institutional barriers to growth. The inability of firms to grow from small to large is a hallmark of relatively poor countries.

Empirical findings on convergence could depend on the definition of leaders. Cette *et al*. (2018) find that in France convergence occurs because a group of firms which were leaders at the start of the sample period suffer a productivity decline, while firms which were initially laggards enjoy productivity growth. But this result is sensitive to the definition of the group of leaders. If it is not fixed and defined as a percentage of the most productive firms in each year, the result is opposite: the gap between leaders and laggards has been increasing since the beginning of the 1990s.

Thus, the convergence process among firms within an industry depends on productivity trends of firms at the higher and lower ends of the productivity distribution. Most recent studies provide evidence of efficiency growth at the frontier. However, overall dynamics will depend on the behavior of lagging firms. If the share of new firms with high growth potential at the lower bound of the productivity distribution is small, then the presence of a large group of non-productive firms which are not exiting the market could impede the convergence process.

While some researchers find an increasing gap in productivity within industries and others find rapid productivity growth at the lower extreme of the initial productivity distribution, the present paper brings together the two different approaches that produce these different results and analyzes both types of convergence phenomena: evolution of dispersion in productivity levels and catch-up of low-productivity firms (higher growth rates at the lower bounds).

The hypothesis we test in this study could be formulated as follows:

H1. Productivity growth rates are positively correlated with the initial productivity gap to the frontier.

H2. Productivity distribution within an industry is very persistent and migration between the quartiles of the distribution is not frequent.

H3. β-convergence does not lead to a reduction of dispersion in productivity levels because (i) the initial productivity gap between leaders and laggards is too wide and (ii) high productivity growth rates are observed only for a tiny share of firms at the lower bound of the productivity distribution. So the rapid improvement achieved by these firms does not translate into a lower dispersion of productivity levels within an industry, i.e. σ-convergence is not observed.

Following the approach of Andrews *et al.* (2016) and Cette *et al.* (2018), we show that in Russia, as in OECD countries and France, firms with low productivity grow faster than those with high productivity. However, taking into account new firms and in particular the permutation of firms, the dispersion indicators suggest that firms diverge from the frontier. We apply stochastic frontier analysis to verify this result. We use two different specifications, both of which confirm that in most industries firms diverge from the frontier.

3. Data

Firm-level data for Russian companies over the years 2011–2016 are taken from Bureau van Dijk's Ruslana database. We carry out analysis for non-farm non-financial market sectors, including mining and quarrying, manufacturing, utilities, wholesale and retail trade, hotels and restaurants, transportation and communications, business services, and personal and other services (see Table 1). We exclude agriculture, construction, financial services and the public sector from our analysis. Factors used or output produced in these sectors differ from the standard set usually taken into consideration (value-added, labor and capital). Therefore, the analysis of these sectors requires a different production function specification, which takes into account additional production factors (as in agriculture) or a set of outputs (as in the public sector).

We do not use data from before 2011 for three reasons. Firstly, requirements for financial reports underwent several changes in 2011. Consequently the data before and after that year are not comparable and cannot be included in one panel. Secondly, size structure of the database changed significantly since 2011 to include more small enterprises and our analysis of convergence requires relatively stable

TABLE 1
List of Sectors and Their Titles

Sector Code	Sector
C	Mining and quarrying
D	Manufacturing
E	Electricity, gas and water supply
G	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods
H	Hotels and restaurants
I	Transport, storage and communication
K	Real estate, renting and business activities
O	Other community, social and personal service activities

size structure (otherwise the changes of the sample would be attributed to the convergence parameters). Thirdly, data on labor costs are not available before 2011, so we cannot calculate value-added for years before 2011.

We exclude firms with fewer than 10 employees, because small firms are insufficiently represented in the Ruslana database. As a result, our unbalanced sample is made up of 34,609 to 71,465 companies per year over the period 2011–2016 (Table 2).

As shown in Table 3, our sample represents on average 25 percent of the employment headcount according to Rosstat. [3]However, the structure of employment in Russia is reproduced adequately: the shares of retail and wholesale trade (sector G) and manufacturing (sector D) are the largest. In terms of value-added the sample represents 30 percent of the total economy reported by Rosstat.[4] Since our sample underrepresents small firms the share of manufacturing (D) is larger, at the expense of retail and wholesale trade (G).

We divide our sample into 173 industries. We begin with as narrow an industry classification as possible. This allows us to assume the same production function for all firms in each industry. However, we have to aggregate some industries until we have a sufficient number of observations for estimating the stochastic frontier model. As a result, most industries are aggregated at the three- or four-digit code of the Russian Classification of Economic Activities (OKVED version 1, which is close to NACE industry classification). The list of industries is presented in the Online Appendix, Table A1.

We use data on operating revenue, fixed assets, employment, the cost of goods sold, labor costs, and the date of incorporation. We use productivity measures based on value-added in line with Andrews *et al*. (2016) and Cette *et al*. (2018). We construct value-added as revenue less cost of goods sold plus labor costs. This reduces our sample quite significantly, because there is less data on labor costs than on other financials. In the value-added concept of productivity only capital and labor are considered as a firm's inputs (OECD, 2001). Energy, materials, services are not considered as a firm's inputs. However in some specifications we use materials as a proxy for intermediate inputs.

We use employment as an approximation of labor input following, Greene (1980), Andrews *et al*. (2016) and Cette *et al*. (2018). Rosstat uses hours worked

[3]Total employment by sectors in 2000–2015 https://rosstat.gov.ru/storage/mediabank/05-05.xls.
[4]Value-added by sectors in 2011–2016 https://rosstat.gov.ru/free_doc/new_site/vvp/vvp-god/tab11.htm.

TABLE 2
NUMBER OF OBSERVATIONS BY YEAR AND SECTOR

Sector		2011	2012	2013	2014	2015	2016
C	Mining and quarrying	916	960	1,226	1,417	1,508	1,378
D	Manufacturing	9,327	9,530	12,707	14,668	15,579	16,376
E	Utilities	2,154	2,136	2,829	3,253	3,543	3,680
G	Wholesale and retail trade	8,930	10,755	17,417	22,544	24,207	25,633
H	Hotels and restaurants	973	978	1,479	1,706	1,875	1,873
I	Transportation and communications	3,172	3,384	4,635	5,405	5,820	6,109
K	Business services	7,531	7,980	11,412	14,457	16,262	17,705
O	Personal and other services	1,606	1,556	2,407	2,671	2,671	2,707
Total		34,609	37,279	54,112	66,121	71,465	75,461

TABLE 3
Sample Representativeness

Employment, 2015

		Number of Employees, ths		Sample as a Share of Rosstat Employment	Share of Sector in Total Employment, Sample	Share of Sector in Total Employment, Rosstat
		Sample	Rosstat			
C	Mining and quarrying	569	1,082	53%	6%	3%
D	Manufacturing	3,366	9,844	34%	33%	24%
E	Utilities	704	1,923	37%	7%	5%
G	Wholesale and retail trade	2,808	12,890	22%	27%	31%
H	Hotels and restaurants	190	1,338	14%	2%	3%
I	Transportation and communications	977	5,501	18%	10%	13%
K	Business services	1,390	6,002	23%	14%	15%
O	Personal and other services	226	2,560	9%	2%	6%
		10,229	41,140	25%	100%	100%

Value added, 2015

		Value Added (2011 Prices), bln rub		Sample as a Share of Rosstat Value Added	Share of Sector in Total Value Added, Sample	Share of Sector in Value Added, Rosstat
		Sample	Rosstat			
C	Mining and quarrying	1,896	5,160	37%	16%	14%
D	Manufacturing	3,309	7,073	47%	29%	19%
E	Utilities	810	1,677	48%	7%	4%
G	Wholesale and retail trade	2,825	8,798	32%	24%	23%
H	Hotels and restaurants	113	484	23%	1%	1%
I	Transportation and communications	884	3,983	22%	8%	10%
K	Business services	1,658	10,175	16%	14%	27%
O	Personal and other services	97	859	11%	1%	2%
		11,592	38,210	30%	100%	100%

to approximate labor input in calculating the official productivity index. This indicator reflects the decisions of firms on the labor market better than number of employees. Russian firms adjust to the changing economic environment not only by hiring in good times and firing in bad times, but often increase or reduce working hours while leaving the number of employees constant. This is a distinctive feature of the Russian economy: as Gimpelson and Kapeliushnikov (2011) argue, the Russian labor market tends to adjust via flexible wages and working hours rather than through increase in unemployment.

However, data on hours worked is available only at the aggregated level. The only available indicator of labor input at firm level is number of employees. We assume that during our sample period 2011–2016 the scale of adjustments via reduction of hours worked was less than in the 1990s or the recession of 2008–2009 (Gimpelson and Kapeliushnikov, 2015). During this period the difference between the rate of growth of the total number of employees[5] and of hours worked[6] in the sectors under consideration was no more than 2.5 percent. Therefore substituting the hours worked by the number of employees during the period 2011–2016 affects the result less than it would do if the study dealt with earlier crisis periods.

Another argument for using number of employees as the labor input indicator is that the employment rigidity differences are larger between sectors than within. Firing workers with job-specific skills is more costly in industrial sectors than in services, so that short-hour regimes are more common in industrial sectors (Gimpelson and Kapeliushnikov, 2011). Our analysis is within narrowly defined industries and we may assume that firms in these industries make similar choices between changing the number of employees or the hours worked. Therefore substituting hours worked by the number of employees does not affect the result as much in our study as it would do in cross-industry analysis.

We use fixed assets as an approximation of capital. Labor productivity is defined as value-added divided by employment. This reflects how efficiently labor input is used to generate value-added. We also use multifactor productivity (MFP) as an alternative measure of productivity. The advantage of MFP is that it reflects efficiency in the utilization of labor and capital inputs combined.

In non-industrial sectors value-added and labor productivity are deflated by the sector-specific value-added deflator. [7]In industry the value-added deflator is available for only three broad sectors: mining (B), manufacturing (C) and utilities (D). However, we observe that variation in producer price indices[8] is quite high between various industries within each of these sectors. Therefore, for industrial sectors we choose the producer price index instead of the value-added deflator because it is much more detailed and is available at the 2 or 3-digit level of OKVED classification.

[5]Total employment by sectors in 2000–2015 https://rosstat.gov.ru/storage/mediabank/05-05.xls. Total employment by sectors in 2016 https://showdata.gks.ru/finder/descriptors/278314.

[6]Hours worked in 2011–2016 https://www.fedstat.ru/indicator/37691.

[7]Gross value-added deflators (basic prices) according to the 2008 SNA methodology (OKVED, 2007) https://fedstat.ru/indicator/57408.

[8]Producer price indices by industries from 2012 to 2016 https://fedstat.ru/indicator/43561.

Capital is deflated by a sector-specific capital price index. We construct the capital price index as a ratio of two indices. The numerator of the ratio is a capital value index[9] in current prices by sectors. It is a base index and reflects growth of fixed asset value compared with the base period (2011). The denominator is the capital volume index[10] by sectors. It is also a base index and reflects price-adjusted growth of fixed asset volume compared with the base period (2011).

4. Productivity Convergence

We begin our productivity convergence analysis with the study of various productivity patterns among groups of leaders and laggards. Recent studies suggest that trends within different productivity groups depend on the definition of these groups (Cette *et al*., 2018). For the groups fixed in the first year of observation, leaders usually show a decline or stagnation in productivity levels, while the least productive companies usually enjoy growth. If productivity groups are redefined each year, then firms from the leading group show faster growth and laggards show much lower growth rates. So the gap in productivity levels between leaders and laggards widens in the case of groups redefined each year. Moreover, this trend is documented for various countries (see Cette *et al*., 2018, for France; Berlingieri *et al*., 2017, for OECD countries; Decker *et al*., 2018 for the US). Also, Gamberoni *et al*. (2016) document a widening gap for the marginal product of labor in EU countries.

Following recent literature, we apply two approaches to define the labor productivity frontier: division with and without renewal. We apply both approaches to the panel of firms which are present in the sample during the whole period 2011–2016, i.e. the balanced panel. Division without renewal implies that groups of firms are defined based on labor productivity in the first year of the sample period. We divide our sample into 10 groups, where the 1st decile represents the least productive firms in 2011 and the 10th decile represents the most productive firms in the same year. Each group is fixed, which is to say that we assign each company to a group once only, in 2011. Afterwards, firms do not migrate into another group regardless of changes in their productivity.

The second, contrasting approach is division with renewal. Here we divide our sample into 10 groups every year. Firms may migrate from one group to another according to changes in their productivity. We then calculate average productivity in each group and compare it with the result for this group in 2011. In this approach it is not important which firms the groups are comprised of. Instead our focus is on the evolution of different deciles of the productivity distribution.

As shown in the literature, division without renewal finds that productivity of leaders declines while productivity of laggards improves. We calculate average accumulated growth in the 1st, 2nd, 7th, and 10th deciles (Figure 2). The best performance is seen in the group of firms with the lowest labor productivity in 2011,

[9]Fixed assets, full book value https://fedstat.ru/indicator/40442.
[10]Fixed assets volume index, price-adjusted https://fedstat.ru/indicator/36733.

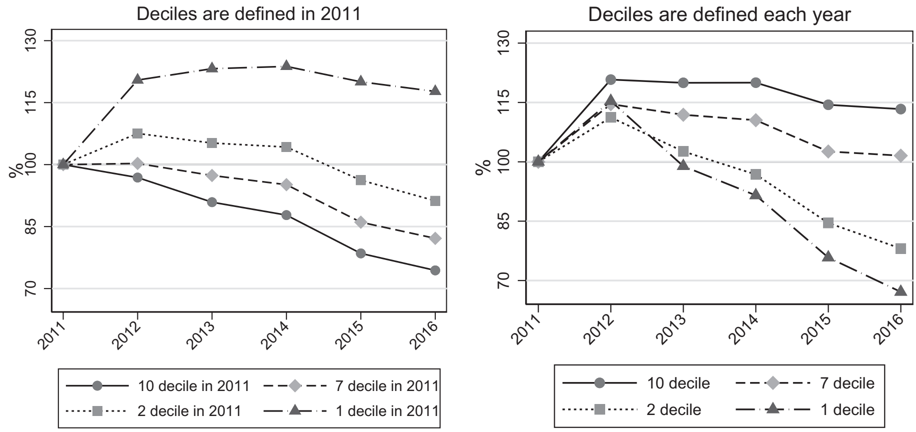

Figure 2. Accumulated Labor Productivity Growth, Frontier without Renewal (Left Panel), Frontier with Renewal (Right Panel)

Notes: 10 decile corresponds to the most productive firms, 1 decile corresponds to the least productive firms.

whereas firms from the 10th, 7th, and 2nd deciles experience a decrease in labor productivity. This can be regarded as an argument for productivity convergence.

Division with renewal yields the opposite results: productivity of the most productive firms grows faster than that of the less productive firms. Average productivity in the most productive deciles improves over the sample period. However, average productivity in the least productive deciles declines.

In the next two sections, we proceed with more formal definitions of convergence that are commonly used in economic literature: β-convergence and σ-convergence.

β-convergence reflects the catching-up behavior of the least productive firms. It is said that the least productive firms converge to the most productive ones if average growth rates are higher for firms from the low-efficiency group. In other words, β-convergence means a positive correlation between the initial productivity gap to the frontier and productivity growth. β-convergence is affected by survival bias because it is estimated based on companies which are found in the sample for two consecutive years.

According to the second concept convergence is assessed by a variance indicator. This approach is called σ-convergence. Unlike β-convergence, which reflects the differences in productivity growth rates with respect to the level of productivity, σ-convergence answers the question, how the distribution of productivity changes over time (Barro *et al.*, 1991). The σ-convergence indicators refer to the reduction of disparities between firms in time. In other words, σ-convergence requires that deviation of labor productivity from the mean decreases, while σ-divergence, on the contrary, implies increase of the productivity dispersion, i.e. a widening gap between productivity leaders and laggards.

One of the most used σ-convergence indicators is dispersion or the coefficient of variation (CV). The main drawback of dispersion or CV as a convergence indicator is its sensitivity to changes of productivity at tails of the distribution. This is the reason why indicators such as the 90-to-10 ratio are also used as σ-convergence indicators. The 90-to-10 ratio is calculated as the difference between the 90^{th} and 10^{th} percentiles of log-productivity. While it is robust to changes in tails of the productivity distribution, the 90-to-10 ratio also indicates divergence when the productivity distribution becomes more dispersed. Unlike β-convergence indicators, σ-convergence indicators are not affected by survival bias.

Young *et al.* (2008) show that β-convergence is not always accompanied by σ-convergence. Strictly stated, β-convergence is a necessary but not sufficient condition for σ-convergence. As Quah (1993) points out, β-convergence does not shed light on evolution of the productivity distribution. It is perfectly consistent with diverging or converging distributions. In other words, σ-divergence may be accompanied by β-convergence. These two concepts could lead to different conclusions because they account differently for exit and entry and for migration between productivity groups.

4.1. β-*convergence*

Macroeconomic literature often refers to β-convergence between countries. Empirical studies on this topic are usually based on long-run time series, covering decades of economic development. A long time series smooths output growth, making results more robust to outliers and macroeconomic shocks. Papers on cross-country convergence usually average output growth over 5-year, 10-year or even longer time periods (Gennaioli *et al.*, 2014; Barro, 2015). Kaneva and Untura (2019), studying convergence between Russian regions, average output growth over a 5-year period, while Perret (2019) and Lehmann *et al.* (2020) use 3-year or 4-year periods.

However, since the firm-level data sets became available only recently, studies on β-convergence within industries cover shorter time spans. Data limitations related to the comparability issues discussed above mean that our sample does not cover a long enough period to smooth our productivity growth estimations. We assume, though, that the nature of firm-level data makes averaging over time periods more challenging in firm-level studies than in cross-country or cross-regional analyses. For example, the group of productivity laggards plays a crucial role in convergence, contributing significantly to productivity growth at the bottom of the productivity distribution. This group is highly heterogeneous (Berlingieri *et al.*, 2020), since it is a transit point for entrants and exiting firms. Therefore averaging productivity growth could magnify the bias towards incumbents, excluding young firms and firms which are about to exit the market.

Consequently we do not average productivity growth for the purposes of β-convergence estimations as is done in other firm-level studies (Andrews *et al.*, 2016; Cette *et al.*, 2018; Gemmell *et al.*, 2018; Berlingieri *et al.*, 2020). Using unsmoothed data leads to estimations of frontier growth that are influenced by macroeconomic shocks. In addition short time span could resulted in the underestimation of technological growth at the frontier. However, we find significant productivity changes at the frontier despite the short-term nature of our estimations.

Following the existing literature that relies on micro-level data, we estimate the correlation between initial distance to the frontier within each narrowly defined

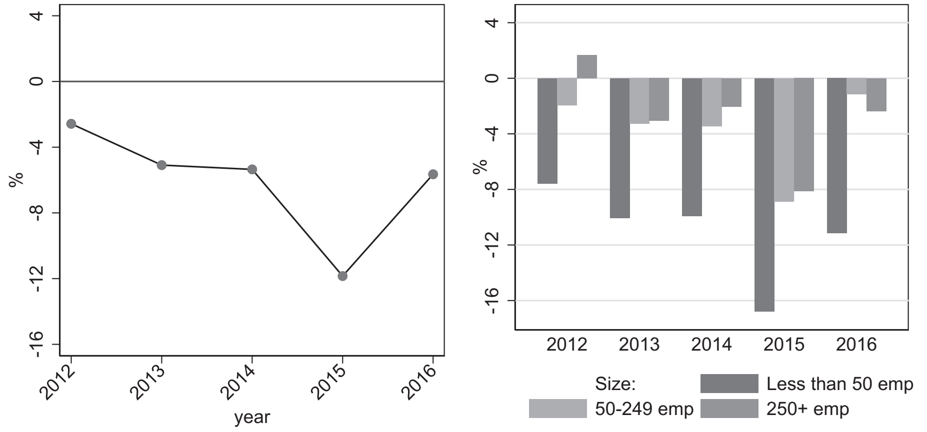

Figure 3. Labor Productivity Growth (Left Panel), Labor Productivity Growth by Size (Right Panel)

industry and productivity growth (β-convergence). We test the hypothesis that laggards grow faster than leaders.

Our calculations show that average labor productivity growth varies by year, sector, size and age, prompting us to include these control variables in the estimations of β-convergence regressions (Figures 3–5). In order to account for differences in mean average growth rates for these dimensions we use the conditional β-convergence approach, which implies that firms converge to the group-specific mean.

In the first step, we estimate the following equation with controls for size, age, sector and year (first specification).

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

where Δlp_{it} is the growth rate of labor productivity of firm i; Δlp_{it} is calculated as the difference between log labor productivity in year t and year $t-1$; gap_{it} is the difference between the logarithm of median productivity of the most productive 5% of firms and the log productivity of firm i in year t (distance to the frontier), since the group of productivity leaders is defined for each industry and year separately (the frontier is year- and industry-specific); $\ln(age_{it})$ is the log age of firm i in period t, allowing us to control for a possible nonlinear relation between age and labor productivity growth; G_p is a dummy variable for pth size (1 for establishments with 10–50 employees; 2 for establishments with 50–250 employees; 3 for establishments with more than 250 employees); Y_j is a dummy variable for the jth year; and S_k is a dummy variable for the kth sector.

A significant positive coefficient on the distance to the frontier gap_{it-1} implies that the worse the initial conditions, the higher the labor productivity growth rate. In other words, it suggests β-convergence.

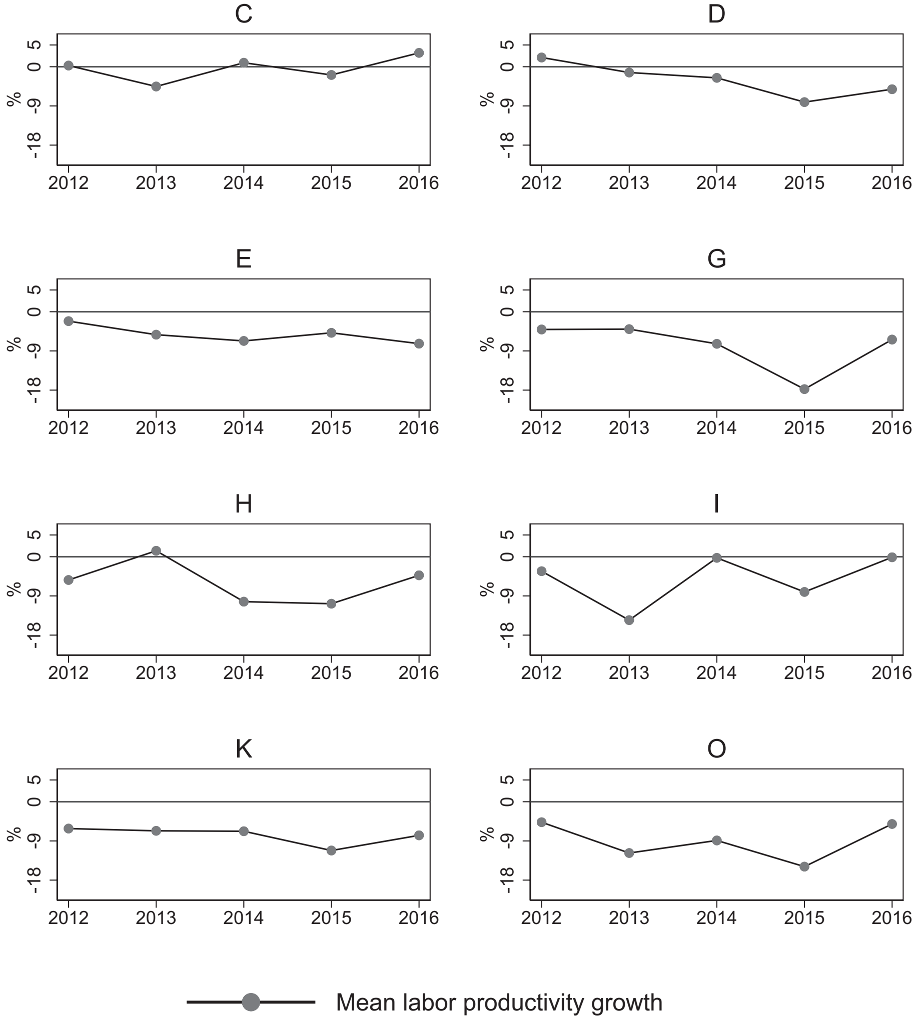

Figure 4. Labor Productivity Growth by Sectors

Notes: C-Mining, D-Manufacturing, E-Utilities, G-Trade, H-Hotels and restaurants, I-Transport and communication, K-Business services, O-Personal and other services.

We run several specifications to check the robustness of the presence of β-convergence to different measures of productivity. We present the results of six specifications of β-convergence in Table 4. The dependent variable in the first three specifications is labor productivity growth. The first specification is presented above, where the independent variable is the lagged gap to the productivity frontier. We also include age, size and year controls. In order to analyze how convergence speed differs between sectors and years we include sector-gap and year-gap interactions in the second specification. In order to analyze how convergence speed differs between size groups and age we include size-gap and age-gap interaction in the third specification.

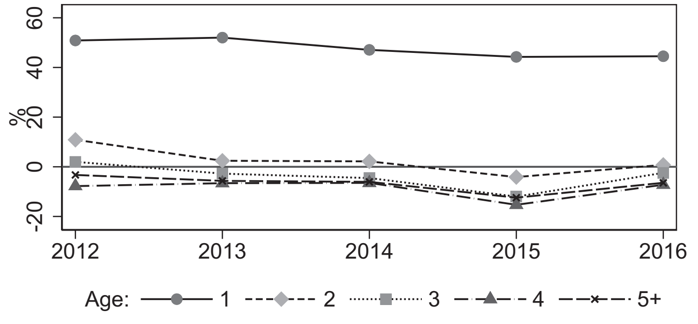

Figure 5. Labor Productivity Growth by Age of Firm

We substitute labor productivity by MFP in the fourth, fifth and sixth specification of the convergence model. We choose the fourth specification following Cette *et al*. (2018). We calculate MFP levels as the ratio of value-added to a geometric average of two inputs, labor and capital: $MFP = \frac{VA}{K^{1-\alpha}L^{\alpha}}$, where α is the average share of labor costs in value-added in each industry. The frontier is defined as median MFP of the 5 percent most productive firms within each industry and year. Productivity growth is defined as the difference between log MFP in year t and year $t-1$. The distance to the frontier is calculated as the difference between the logarithm of the median MFP of 5 percent of the most productive firms in the industry and the log productivity of each firm in this industry.

We choose the fifth specification for the β-convergence model following Andrews *et al*. (2016). As in the previous specification we estimate MFP levels as the ratio of value-added to a geometric average of two inputs, labor and capital: $MFP = \frac{VA}{K^{\beta}L^{\alpha}}$. However in this case we estimate the production function in order to obtain labor and capital shares as elasticities of value-added with respect to labor and capital. We employ the estimation method proposed by Wooldridge (2009), which builds on Levinsohn and Petrin (2003) but avoids a two-stage technique. This method addresses the problem of simultaneous determination of labor input and productivity by using intermediate inputs and lagged values of endogenous inputs as instrumental variables. We follow the use of this approach by Petrin and Levinsohn (2012). We instrument labor with its lagged value. Unobserved productivity is approximated by a third-order polynomial in capital and materials. The production function is estimated separately for each narrowly defined industry. The frontier is defined as mean MFP of the 5% most productive firms within each industry and year. Productivity growth is calculated as the difference between log MFP in year t and year $t-1$. The distance to the frontier is defined as the difference between the logarithm of the mean MFP of the 5 percent most productive firms in the industry and the log productivity of each firm in this industry.

In the fifth specification we include growth at the frontier as a control variable, as in Andrews *et al*. (2016). Growth at the frontier may be considered as industry–year control, since it varies within a particular industry only with years, but not with firms. We also modify the fifth specification adding interactions between the distance to the frontier in the previous period and size dummies, age, and growth

TABLE 4
Estimation Results of β-Convergence

	(1)	(2)	(3)	(4)	(5)	(6)
	LP	LP	LP	MFP	MFP	MFP
gap_{t-1}	0.03***	0.05***	0.09***	0.04***	0.08***	0.15***
	(0.001)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
frontier_growth					0.17***	0.27***
					(0.007)	(0.015)
Year						
2013	−0.03***	−0.04***	−0.04***	−0.05***	−0.01	0.01
	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
2014	−0.02***	−0.03***	−0.03***	−0.06***	−0.00	0.01
	(0.004)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
2015	−0.08***	−0.10***	−0.10***	−0.13***	−0.06***	−0.05***
	(0.003)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)
2016	−0.01***	−0.03***	−0.03***	−0.06***	−0.00	0.00
	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Sector						
D	−0.01	0.07***	0.07***	0.06***	0.05***	0.05***
	(0.007)	(0.015)	(0.015)	(0.017)	(0.014)	(0.014)
E	−0.03***	−0.02	−0.01	−0.01	0.01	0.03
	(0.008)	(0.016)	(0.016)	(0.019)	(0.016)	(0.016)
G	−0.07***	0.04***	0.05***	−0.02	0.02	0.04***
	(0.007)	(0.015)	(0.015)	(0.017)	(0.014)	(0.014)
H	−0.03***	0.04**	0.05**	0.02	0.05**	0.06***
	(0.009)	(0.02)	(0.02)	(0.021)	(0.019)	(0.019)
I	−0.02**	0.002	0.01	0.02	−0.01	−0.00
	(0.007)	(0.016)	(0.016)	(0.018)	(0.015)	(0.015)
K	−0.04***	0.01	0.02	0.01	0.02*	0.03*
	(0.007)	(0.015)	(0.015)	(0.017)	(0.014)	(0.014)
O	−0.03***	0.02	0.02	−0.03	0.02	0.02
	(0.008)	(0.017)	(0.017)	(0.02)	(0.017)	(0.017)
Size						
50–249 emp	0.10***	0.10***	0.11***	0.14***	0.14***	0.11***
	(0.002)	(0.002)	(0.005)	(0.003)	(0.003)	(0.006)

(Continues)

TABLE 4 (CONTINUED)

	(1)	(2)	(3)	(4)	(5)	(6)
	LP	LP	LP	MFP	MFP	MFP
250+ emp	0.10***	0.10***	0.14***	0.18***	0.17***	0.17***
	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.006)
ln(age)	−0.05***	−0.05***	−0.02***	−0.07***	−0.07***	−0.00
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
frontier_growth*gap_{t-1}						−0.04***
						(0.005)
constant	−0.03***	−0.08***	−0.18***	−0.01	−0.12***	−0.28***
	(0.008)	(0.015)	(0.017)	(0.018)	(0.015)	(0.016)
N	201,920	201,920	201,920	201,914	201,863	201,863
Average marginal effect of gap_{t-1}	0.03	0.03	0.03	0.04	0.06	0.06

Notes: standard errors in parentheses. In regression 4 and 5 we use ***MFP*** growth instead of labor productivity growth following Cette *et al*. (2018) and Andrews *et al*. (2016) respectively. Reference categories: 2012, Mining and Quarrying, less than 50 employees.

*p < 0.10 **p < 0.05, ***p < 0.01.

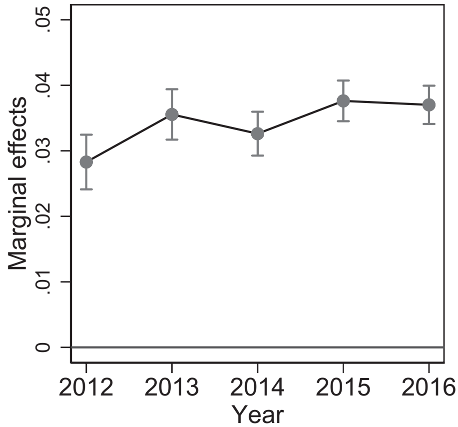

Figure 6. Speed of β-Convergence by Year (Left Panel), and sector (Right Panel)
Notes: average marginal effects with 95% confidence intervals.

at the frontier. As result we have the sixth specification, which allows us to analyze whether convergence speed changes with growth at the frontier.

Table 4 shows the results of β-convergence estimations. The bottom row presents average marginal effect on productivity growth of the gap in the previous period, in other words, the average change in productivity growth with respect to the change in the gap in the previous period. It lies in the range of 3–6 percent. Estimations made by Cette *et al*. (2018) for France are higher (about 10 percent). So the average rate of convergence in the Russian economy is quite low and closer to estimates of convergence rates among countries (about 2 percent) than to convergence rates in an economy with developed markets (Abreu *et al*., 2005).

We find positive correlation between the gap to the frontier and productivity growth in all sectors and all years (column 2). We do not observe a convergence slowdown in 2012–2016 (Figure 6), in contrast with the estimations of Cette *et al*. (2018) who report a sharp decline in the speed of β-convergence in the post-crisis period. The speed of β-convergence varies for different sectors (see Figure 6, right panel). Manufacturing (sector D) and Trade (sector G) show the lowest rates of β-convergence (2–3 percent). These two sectors drag the average β-convergence rate down, since their shares in our sample are the highest. In other sectors the β-convergence rate is higher. The highest rates (about 6%) are found in Mining (sector C) and Utilities (Sector E). However, even in these sectors the rate is lower than the estimated convergence rate for France (Cette *et al*., 2018).

Our results (column 3) suggest that convergence speed is higher among small firms with less than 50 employees and decreases with size (Figure 7). We also find (column 3) that convergence of young firms is significantly higher than that of older establishments (Figure 7). Age has negative effect on both labor productivity growth (column 1–2) and speed of convergence (column 3).

Since we assume that productivity growth depends on the gap to the frontier in the previous period, we can calculate half-life to convergence with the frontier by applying the exponential decay formula: $t = \frac{\ln(2)}{\lambda}$, where $\lambda = -\ln(1-\mu)$ and μ is marginal effect of the gap to the frontier on labor productivity growth calculated

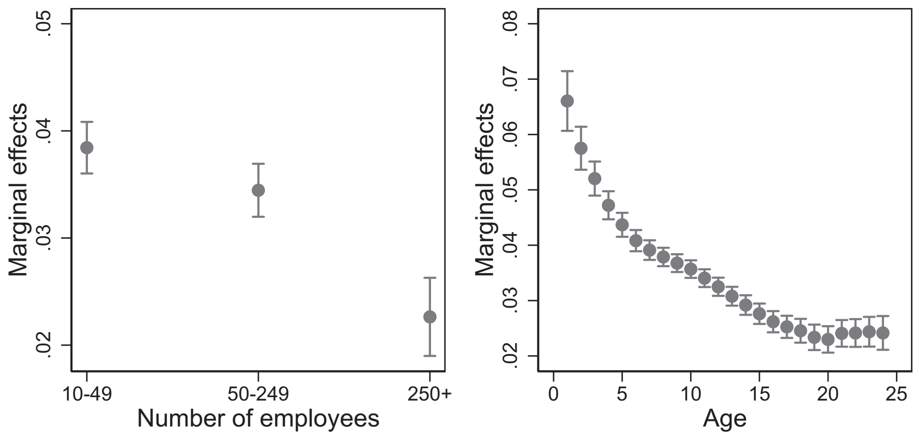

Figure 7. Speed of β-Convergence by Size (Left Panel), and by Age of Firm (Right Panel)
Notes: average marginal effects with 95% confidence intervals.

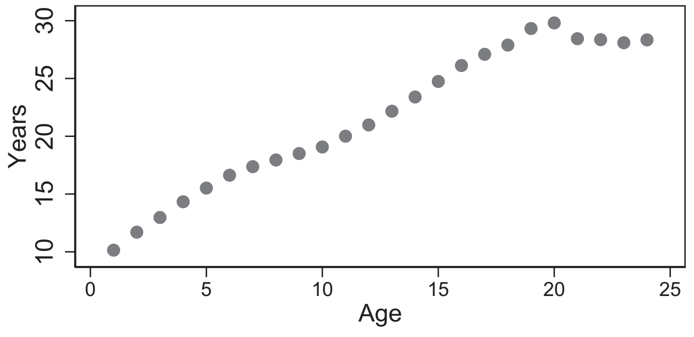

Figure 8. Half-Life of Convergence with Frontier

at different values of a firm's age (see, for example, Eckey *et al*., 2007). We find that it takes a new firm about 10 years to halve the distance to the frontier (Figure 8). But in the case of a five-year-old firm it takes significantly more, almost 16 years, to halve the distance to the frontier.

We show that application of the β-convergence model to labor productivity and to MFP yields similar results with slightly higher convergence speed in the MFP case (column 4–6). The results suggest positive correlation between MFP growth at the frontier and average growth of the rest of the firms in an industry (column 5). Nevertheless as MFP growth at the frontier increases the convergence speed slows down (column 6). This means that rapid MFP improvement by leaders does not stimulate other firms to converge. On the contrary, if the leaders do not grow fast it is easier for the rest to catch up with them.

Summarizing the results of various specifications, we conclude that β-convergence in the Russian economy is mainly driven by the catching up of young new firms. Indeed, the share of firms with high-productivity growth among young firms is significantly higher than the share in other age groups (Figure 9), and the distribution

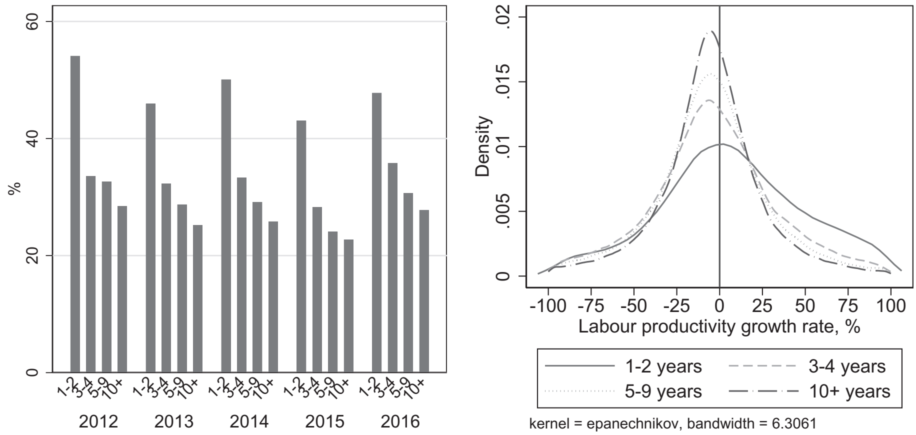

Figure 9. Share of Firms with Labor Productivity Growth of more than 10% by Age Group (Left Panel), Density of Labor Productivity Growth by Age Group (Right Panel)

of labor productivity growth rates for young firms has a fat tail at positive values. However, as the age of the survivals increases the rate of convergence slows down, so that older firms stagnate without reaching the productivity levels of frontier companies. These results are in line with the findings of Haltiwanger *et al*. (2013), who show a large contribution of surviving young firms to net growth for the U.S. In fact, Decker *et al*. (2014), also using U.S. data, show that this group of enterprises is extremely uneven and the share of firms with very high growth rates is not large.

4.2. σ-*convergence*

The recent literature shows that productivity is highly heterogeneous even in narrowly defined industries. Moreover, the gap is increasing despite negative correlation between the productivity level and its growth. This means that β-convergence is accompanied by σ-divergence.

For example, Berlingieri *et al*. (2017) report σ-divergence of productivity based on firm-level data from OECD countries. The main indicator of dispersion they use is the 90-to-10 ratio (the difference between the 90th and 10th percentiles of log-productivity). This indicator takes into account change in the whole sample, including firms which are present in the sample for less than two consecutive years, which are neglected by the β-convergence indicator. Berlingieri *et al*. (2017) calculate this ratio for manufacturing and services for 16 countries[11] in 2011.

The left panel of Figure 10 shows that the log of the ratio in our sample was 3.48 in 2011. The dots represent the unweighted average 90-to-10 ratio in manufacturing and services in 2011 calculated by Berlingieri *et al*. (2017). We find that in Russia in 2011 the ratio was higher than the average for 16 countries. It was also higher than in all the countries in the sample used by Berlingieri *et al*. (2017), except for the services

[11] The sample includes: Australia, Austria, Belgium, Chile, Denmark, Finland, France, Hungary, Indonesia, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Sweden.

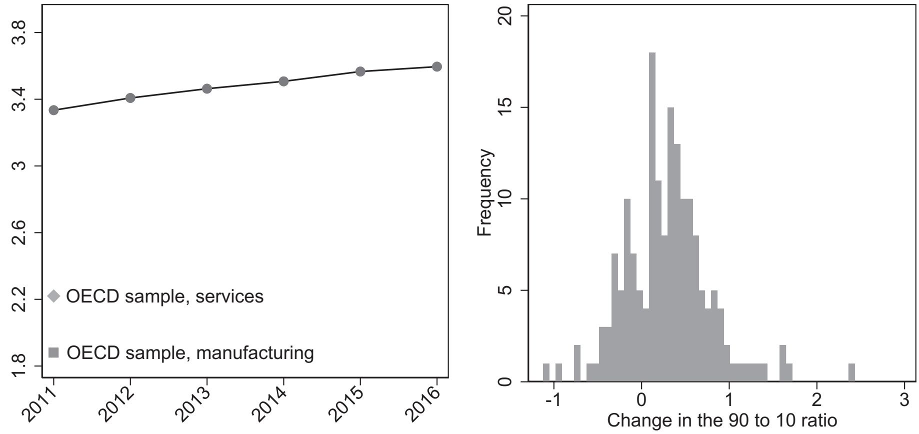

Figure 10. Ratio of Labor Productivity of the 10th to the 1st Decile, Division with Renewal, Logarithmic Scale (Left Panel), change in the labor productivity 90-to-10 ratio in 173 industries in 2011–2016 (Right Panel)

Notes: dots on the left correspond to the 90-to-10 ratio in 2011 reported in Berlingieri *et al*. (2017) as an unweighted average for several countries. The sample includes: Australia, Austria, Belgium, Chile, Denmark, Finland, France, Hungary, Indonesia, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Sweden.

sector in Chile. The estimates for the U.S. are also lower: 1.9 in 1997–2010 reported by Cunningham *et al*. (2018) and 1.4 in 1977 reported by Syverson (2004). The relatively high level of productivity dispersion may be associated with high regional segmentation in Russia (Gennaioli *et al*., 2014, see Figure 11). We find that during the whole sample period the gap remains substantially higher than Berlingieri *et al*. (2017) present. Moreover, the ratio increased over the sample period.

The right panel of Figure 10 summarizes the difference between the labor productivity 90-to-10 ratio in 2016 and in 2011 across 173 industries in the sample. Unlike Griffith *et al*. (2009), we find that dispersion increased over the sample period in most industries. Mining and quarrying (sector C) saw the highest ratio growth. This suggests that mining and quarrying experienced the most rapid divergence of labor productivity.

We also check the persistence of the position of a firm in the distribution of labor productivity. To construct the transition matrices, we estimate a dynamic multinomial model. The dependent variable is the resulting productivity quartile, while the explanatory variables are the productivity quartile in the previous year and controls for age and size. As Wooldridge (2005) points out, in this type of model the treatment of a lagged dependent variable as exogenous is an issue known as the initial condition problem. The GMM framework is normally used to solve this problem in the case of linear models. However, in nonlinear models, such as our dynamic multinomial model, the initial condition problem is more complicated. In order to solve this problem Wooldridge (2005) proposes controlling for unobserved heterogeneity by including in the regression the initial value of a dependent variable as well as initial and average values of exogenous variables. We follow Skrondal and Rabe-Hesketh (2014) and implement the Wooldridge (2005) approach. As result, we estimate the following model:

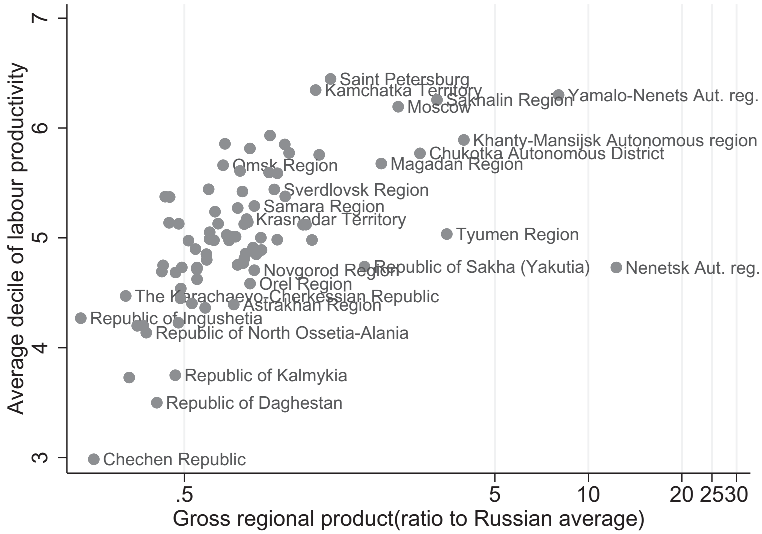

Figure 11. Performance of Firms and Regions

Notes: The figure illustrates correlation between performance of regions and individual performance of firms in the respective region in 2016. The y-axis depicts deciles averaged by firms located in each region regardless of the industry. The x-axis depicts the ratio of gross regional product (GRP) per capita to the Russian average (logarithmic scale). We find that this measure of firm performance is positively correlated with the ratio of GRP to the Russian average.

$$PR(Qt_{it} = k) = \frac{\exp(\boldsymbol{\beta_k X})}{1 + \sum_{m=1}^{3} \exp(\boldsymbol{\beta_m X})}$$

where Qt_{it} is a productivity quartile of firm i in year t, k takes values from 1 to 3, and the fourth (most productive) quartile is treated as a baseline outcome. $\boldsymbol{X}$ is a vector of explanatory variables and controls. $\boldsymbol{X}$ includes: the productivity quartile in the previous year Qt_{it-1}; age of firm i in year t (age_{it}); two dummy variables for size categories 2 (50–250 employees) and 3 (more than 250 employees) ($size_{it}$). $\boldsymbol{X}$ also includes initial values of these variables: the initial quartile, age and two dummies for size. Moreover, $\boldsymbol{X}$ includes the average values of exogenous variables: age and two dummies for size.

We follow Wooldridge (2005) and Skrondal and Rabe-Hesketh (2014) by including only observations which are part of a consecutive sequence of at least two non-missing records. We estimate this model separately for each sector. (We present the results in the Online Appendix, Table A2). The dynamic multinomial model enables us to predict modeled probabilities of inclusion in a particular quartile of productivity distribution given the previous quartile and controls (Table 5).

Transition matrices between quartiles illustrate that the group of the most productive firms is relatively stable. For example, 81 percent of the most productive firms (the 4th quartile) in 2011 remain in the same quartile in 2012. In the following years, the share of the most productive firms remaining in the 4th quartile is even higher at 84–85 percent. Moreover, the share of firms from the 3rd quartile improving to the 4th quartile is no more than 14 percent. As in cross-country studies (Islam, 2003), we find that productivity is highly persistent.

TABLE 5
Transition Matrices Between Quartiles of Labor Productivity Distribution Simulated from a Dynamic Multinomial Model

		2012							2013				
		4	3	2	1				4	3	2	1	
2011	4	81%	17%	2%	1%	100%	2012	4	85%	13%	1%	1%	100%
	3	12%	69%	17%	2%	100%		3	14%	68%	16%	2%	100%
	2	1%	14%	71%	13%	100%		2	2%	16%	69%	14%	100%
	1	1%	2%	14%	84%	100%		1	1%	2%	16%	82%	100%
		2014							2015				
		4	3	2	1				4	3	2	1	
2013	4	84%	13%	2%	1%	100%	2014	4	84%	13%	2%	1%	100%
	3	13%	68%	17%	2%	100%		3	12%	67%	18%	3%	100%
	2	2%	15%	68%	15%	100%		2	2%	15%	68%	16%	100%
	1	1%	2%	14%	83%	100%		1	1%	2%	14%	84%	100%
		2016											
		4	3	2	1								
2015	4	84%	13%	2%	1%	100%							
	3	12%	67%	18%	3%	100%							
	2	2%	14%	66%	18%	100%							
	1	1%	2%	13%	84%	100%							

Notes: firms in the fourth quartile are the most productive in terms of labor productivity, firms in the first quartile are the least productive in terms of labor productivity. Transition matrices illustrate the share of firms which transit from quartile to quartile in each year.

Using labor productivity data, we show that laggards grow faster than leaders on average. However, we found that the rate of β-convergence decreases with firms' age, making the survivors unable to get significantly closer to the frontier firms. Moreover, despite the presence of β-convergence (i.e. catching up by the least productive firms) we find that with all firms, including those new in the sample, taken into account, the gap between the most and the least productive firms has increased over the post-crisis period. The persistence of productivity levels means that fast productivity growth at the lower bound of the productivity distribution (driven mostly by young firms) is not sufficient to enable convergence.

5. Multifactor Productivity Convergence In The Stochastic Frontier Model

In this section, we apply stochastic frontier analysis (SFA) to verify the result concerning divergence dynamics which was obtained in the previous section. SFA makes it possible to simultaneously estimate MFP growth and relative efficiency of a firm and its evolution, because convergence parameters are explicitly included in the specifications. In this type of model, the leaders (i.e. firms closest to the stochastic production possibility frontier) are defined using information on performance by firms during the entire sample period. Hence the stochastic frontier approach is more robust (than σ-divergence indicators) to the choice of leaders and the definition of laggards.

We adopt the panel production frontier model with a translog specification:

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

where y_{it} is the logarithm of value-added of firm i in period t, l_{it} is the logarithm of the labor force, k_{it} is the logarithm of capital used, t is the period of time, v_{it} is the error term, $v_{it} \sim N\left(0, \sigma_v^2\right)$, $u_{it} \geq 0$ represents technical inefficiency. The deterministic part of the production function represents the production frontier, i.e. the highest level of production at given levels of labor and capital.

We adopt two types of specifications for the inefficiency part:

1. the time varying decay specification following Battese and Coelli (1992)

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

where u_i is the time invariant component of inefficiency, $u_i \sim N^{+}(0, \sigma_u^2)$, $G(t)$ is the time function, γ is the decay parameter, and T is the terminal period. Here γ is the parameter indicating convergence or divergence. If $\gamma < 0$, then firms converge to the frontier, and if $\gamma > 0$, then firms diverge from the frontier. The model ignores temporary productivity deviations. It smooths fluctuations of productivity, so that only firms with constantly high productivity levels are regarded as leaders.

2. the modified Kumbhakar (1990) model

$$u_{it} = G(t)\, u_i,\, G(t) = \left[1 + \exp\left(\sum_{j=2012}^{2016} \beta_j * Y_j\right)\right]^{-1},$$

where u_i is the time invariant component of inefficiency, $u_i \sim N^+(0,\ \sigma_u^2)$, $G(t)$ is the time function, and Y_j is a dummy variable for the j th year.

The crucial difference between the two specifications is flexibility. In the first specification, we assume a smooth exponential increase or decrease of technical efficiency. Therefore, we impose restrictions on the evolution of technical efficiency. We parametrize it with just one coefficient γ (the decay parameter). In the second specification, we relax this assumption. We assume that technical efficiency may fluctuate from year to year. We introduce dummy variables for each year reflecting a different gap to the frontier in each year.

We estimate the time varying decay specification for all 173 industries in our sample. For the second specification with the year dummies in the inefficiency term (Kumbhakar 90), the estimation procedure was not converged for twelve industries.

In the case of two stochastic frontier models, we estimate MFP growth rates for each firm as a sum of three components: technical progress ($T\Delta$), change in the efficiency level of a firm and the return-to-scale term (for details, see Kumbhakar and Lovell, 2003). Technical progress represents MFP growth due to move of the production frontier, i.e. of the maximum level of production given inputs. Change in the efficiency level reflects MFP growth due to change in relative position to the production frontier.

In Figure 12, we present the average MFP growth rates for both specifications and compare them with labor productivity growth and MFP growth calculated following Andrews *et al*. (2016) (see section 4). Estimations of MFP growth as part of both stochastic frontier models are relatively close to labor productivity growth and non-stochastic MFP growth. The first model produces a smooth decline of MFP growth due to a rigid specification of the technical efficiency component. The second model yields more volatile MFP growth because the second specification allows technical efficiency to fluctuate each year. As a result, the first specification extrapolates the negative trend to the last year of the sample, while the second specification indicates some recovery in 2016, which is in line with the evolution of labor productivity and non-stochastic MFP.

In the time varying decay model (the first specification), we parametrize convergence with γ as a decay parameter. Positive γ indicates divergence, and negative γ indicates convergence. In most industries in our sample, we find positive γ (we present detailed estimation results in the Online Appendix, Table A3). This means that technical efficiency worsened over the sample period and companies diverge from the frontier. As Figure 13 shows, out of 173 industries examined we find 139 with a statistically significant positive decay parameter (we show results with the opposite sign for comparability purposes). This indicates that firms diverge from the frontier. In the rest of the industries we find an insignificant parameter γ, suggesting no evidence for convergence.

In the modified Kumbhakar 90 (the second specification), we parametrize convergence with a set of year dummies (β_j) instead of a single decay coefficient. Positive β_j indicates that the average distance to the frontier in year j was shorter than in the baseline year (2011), while negative β_j indicates a widening gap in year j relative to 2011. The results of the second specification (modified Kumbhakar 90) indicate that technical efficiency worsened in most of the industries over the sample

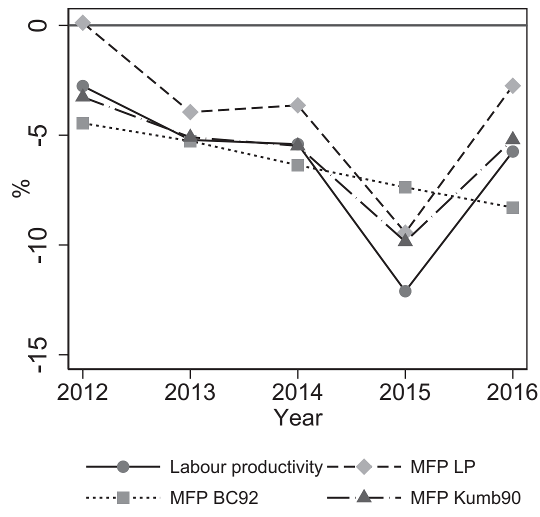

Figure 12. Average Productivity Growth Rates Estimated Using Different Methodologies

Notes: labor productivity (LP) growth is calculated as log difference of labor productivity. Multifactor productivity growth LP is estimated following Andrews *et al*. (2016) and Petrin and Levinsohn (2012) as output growth unexplained by input growth. Shares of factor inputs are estimated via the production function. Labor is instrumented with its lagged values, while unobserved productivity is approximated by a third-order polynomial in capital and materials. MFP BC92 growth is estimated as a sum of three components: technical progress, technical efficiency change, and scale effect. The inefficiency specification is a time decay model following Battese and Coelli (1992). In order to estimate MFP Kumb90 growth, we use the modified Kumbhakar90 model with dummy variables for each year as an inefficiency specification. For technical progress, technical efficiency change and scale effect calculation we use discrete increments instead of derivatives.

period (we present detailed estimation results in the Online Appendix, Table A4). In 94 industries out of 161, we find a negative coefficient for the 2016 dummy variable in the inefficiency term, meaning that the distance to the frontier increased. Technical efficiency improves in only 5 industries in 2016 relative to 2011. In the remaining 62 industries, change in technical efficiency is insignificant (Figure 13).

Thus, the Kumbhakar 90 specification, which is more flexible than the time varying decay model, supports our conclusion that most of the industries in our sample show divergence of technical efficiency.

Despite the fast productivity growth of laggards found previously (β-convergence), the gap to the frontier increases in most industries. This is confirmed by σ-convergence indicators and stochastic frontier models. In the latter case, we estimate two different specifications: with divergence parametrized by a single coefficient (a smooth decline or improvement in the gap to the frontier) and with divergence parametrized for each year in the sample separately. The results of both specifications show that in most industries technical efficiency decreased over the sample period, i.e. firms diverged from the frontier. So the catch-up momentum of young, low-productivity firms is not sufficient for convergence by reduction of the distance to the frontier.

We compare the performance of industries in which firms do not diverge from the frontier with industries where there is divergence (according to our first specification). To do so, we compare industries that come within the same broader class of industries (mainly at the two-digit level of OKVED) and that show absence

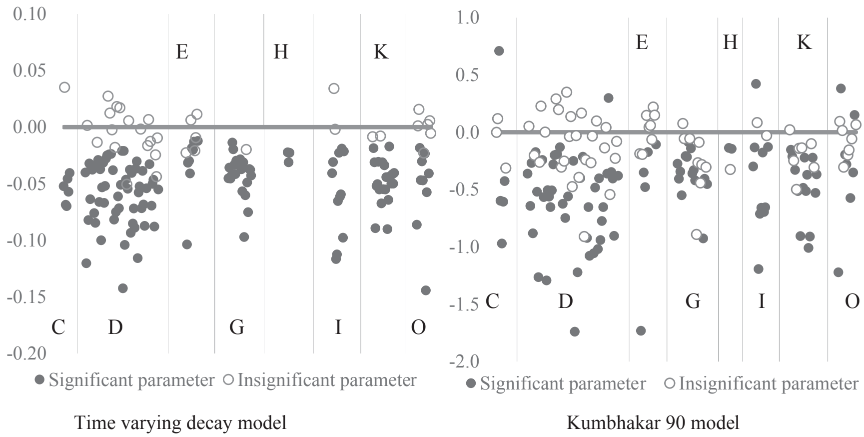

Figure 13. Estimated Convergence Parameters of the Time Varying Decay Model by Industry (with the Opposite Sign) (Left Panel), Estimated Convergence Parameters of Modified Kumbhakar 90 Model by Industry (Right Panel)

Notes: The left-hand graph presents the estimated decay parameter γ for each industry in the first specification (Battese and Coelli, 1992), where γ is introduced in the inefficicency specification in the following way: $u_{it} = G(t)\, u_i, G(t) = e^{\gamma(t-T)}$. Positive γ means divergence, negative γ means convergence. We present it with the opposite sign for comparability. The right-hand graph presents the estimated dummy coefficients for 2016. We modify the Kumbhakar 90 specification, instead of time and time squared we include year dummies in the inefficicency specification in the following way: $u_{it} = G(t)\, u_i$, $G(t) = \left[1 + \exp(\sum_{j=2012}^{2016} \beta_j * Y_j)\right]^{-1}$. Positive β_{2016} means that the average efficiency in 2016 was greater than in 2011, in other words, the gap between the frontier and laggards decreased.

and presence of divergence. For example, we find no divergence in "Mining and agglomeration of lignite and peat" (industry code 10.2 + 10.3), but in "Mining and agglomeration of hard coal" (industry code 10.1) we find that firms diverge from the frontier. We compare firms from these two industries within the broader industry (higher level of aggregation of industry classification) "Mining of coal and lignite; extraction of peat" (industry code 10).

According to our results there are 22 broad industries that include both groups of industries with and groups without divergence (Table 6).

We are interested whether technical progress ($T\Delta$) is different between these two groups within broad industries. We run the Student's t-test, where the null hypothesis is that mean technical progress is equal between industries with and without divergence. We find that the null hypothesis is not rejected in only three broad industries. In most broad industries (19 out of 22) the alternative hypothesis that mean technical progress in divergence industries is greater than in non-divergence industries is not rejected. In other words absence of divergence is associated with a smaller change in technical progress. This means that lack of divergence in these industries is due to absence of growth at the frontier rather than to a stronger catching up process among low-productivity firms. However, in industries where most firms diverge from the frontier, productivity growth of leaders is stronger than in industries with no divergence.

This result confirms our conclusion reported in Section 4.1 above. High growth at the frontier does not stimulate firms below the frontier to catch up. On the contrary, it impedes convergence. In the sample of Russian firms the absence of divergence is

TABLE 6
Results of Student's t-Test for Equality of Means of Technical Progress in Industries with Divergence and Without Divergence

Broad Industry	Broad Industry (NACE Codes)	Number of Observations in Broad Industry	Industries (NACE Codes) with Divergence	Industries (NACE Codes) without Divergence	Mean $T\Delta$ in non Divergence Industries	Mean $T\Delta$ in Divergence Industries	p-Value (Mean $T\Delta$ in non Divergence Industries < Mean $T\Delta$ in Divergence Industries)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mining of coal and lignite; extraction of peat	10	871	101	102 + 103	−0.07	0.10	1
Manufacture of food products	15	16,096	151 152 154 155 156 157 158 159	153	−0.04	0.04	1
Manufacture of textiles	17	1,352	171 + 172 174 175	176 + 177	−0.01	0.04	1
Manufacture of rubber and plastic products	25	4,380	252	251	0.00	−0.01	0.01
Manufacture of other non-metallic products	26	7,903	262 + 263 264 266 268	261 265 267	0.03	0.05	1
Manufacture of basic metals	27	1,935	271 273	272	−0.03	0.05	1
Manufacture of fabricated metal products, except machinery and equipment	28	7,060	281 282 283 285 287	284 286	0.02	0.01	0.01
Manufacture of machinery and equipment, n.e.c.	29	8,565	293 294 295 2911 2912 2913 2921 2922 2923 2924	297	−0.04	0.03	1

(Continues)

TABLE 6 (CONTINUED)

Broad Industry	Broad Industry (NACE Codes)	Number of Observations in Broad Industry	Industries (NACE Codes) with Divergence	Industries (NACE Codes) without Divergence	Mean $T\Delta$ in non Divergence Industries	Mean $T\Delta$ in Divergence Industries	p-Value (Mean $T\Delta$ in non Divergence Industries < Mean $T\Delta$ in Divergence Industries)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Manufacture of electrical machinery and apparatus n.e.c.	31	3,883	311 312 313 314 315	316	−0.04	0.05	1
Manufacture of motor vehicles, trailers and semi-trailers	34	2,079	342 343	341	−0.10	0.03	1
Manufacturing of furniture; manufacturing n.e.c.	36	2,427	361	362 365 366	−0.03	0.04	1
Land transport; transport via pipelines	60	10,195	601 602	603	−0.05	−0.02	1
Water transport	61	1,035	612	611	0.02	0.01	0
Real estate activities	70	31,315	702 703	701	−0.04	0.01	1
Computer and related activities	72	6,056	721 722	723	0.02	0.06	1
Sewage and refuse disposal, sanitation and similar activities	90	4,553	9000 9003	9001 9002	−0.09	−0.03	1
Recreational, cultural and sporting activities	92	5,441	921 922 923 + 925 926 927	924	−0.02	−0.01	1
Other service activities	93	3,374	9301 9303	9302 9304 9305	−0.08	−0.01	1

(Continues)

TABLE 6 (CONTINUED)

Broad Industry	Broad Industry (NACE Codes)	Number of Observations in Broad Industry	Industries (NACE Codes) with Divergence	Industries (NACE Codes) without Divergence	Mean $T\Delta$ in non Divergence Industries	Mean $T\Delta$ in Divergence Industries	p-Value (Mean $T\Delta$ in non Divergence Industries < Mean $T\Delta$ in Divergence Industries)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Other retail sale of new goods in specialized stores	524	4,961	5241 5242 5243 5244 5246 5247 5248	5245	−0.11	−0.02	1
Production of electricity	4011	812	40115	40111	0.08	0.11	1
Distribution and sale of electricity	4013	2,205	40131 40132	40133	−0.07	0.08	1
Steam and hot water supply	4030	7,343	40300 40301	40302 40303 40304 + 40305	−0.06	−0.06	0.99

Notes: The table presents evidence of different pace of technical progress in industries with and without divergence. Column 1 and 2 present the broad industries and their NACE codes. The number of observations is reported in column 3. The broad industry in each row of the table includes narrowly defined industries featuring the absence (column 4) and presence (column 5) of divergence. Column 6 and 7 report the mean technological progress of these two groups of narrowly defined industries, respectively. We run Student's t-test for the equality of two means. The alternative hypothesis: technical progress is faster in the group of industries where we find divergence from the frontier. The p-value of this hypothesis is presented in column 8. In most cases (19 out of 22), technical progress in the group of industries with divergence is faster than in industries where there is no divergence.

not the result of intensive knowledge diffusion. On the contrary, we do not find divergence in those industries where productivity of all firms grows insufficiently.

One possible explanation is that rapid advance of the frontier entails a higher required growth rate in order to catch up. As convergence becomes more difficult, firms below the frontier lose incentives and do not attempt to increase their efficiency. By contrast, low growth at the frontier makes it easier to converge, encouraging firms below the frontier to make the effort to catch up.

On the other hand, absence of divergence together with slow growth at the frontier indicates poor performance of all firms in the industry. For example, if competition in an industry is too strong and all firms operates at zero profit margin, they lack resources to finance innovation and move up the frontier in their industry. Another reason for the absence of growth at the frontier could be the presence of institutional barriers to entry that reduce competition in an industry and discourage innovation behavior of both leaders and laggards. In this case no divergence means absence of opportunities for the industry as whole to grow. Fast growth at the frontier, on the contrary, indicates, that there is some scope for growth. The most efficient firms use this opportunity, diverging from the rest of the firms.

6. Conclusions

Almost all studies that examine the correlation between the productivity level and growth of productivity find β-convergence. This means that, on average, low-productivity firms grow faster than high-productivity firms. On the other hand, the literature shows that even in narrowly defined industries, the gap between leaders and laggards is wide and persistent, which suggests that rapid growth of laggards relative to other groups of firms does not lead to narrowing of the gap. Instead, σ-convergence, i.e. increasing dispersion of productivity, is found in a number of studies.

We combine two approaches to convergence analysis and demonstrate that this result also holds for Russian firms. On the one hand, we have found that low-productivity firms show higher productivity growth rates on average (so-called β-convergence). On the other hand, despite the confirmed β-convergence, the gap between the leaders and the laggards in the Russian economy is large, wider than that reported for other countries. In addition, over the period of observation, the gap continues to grow, suggesting divergence in productivity levels (i.e. σ-divergence).

The lack of convergence has two causes. First, the share of very efficient, fast-growing firms appears to be tiny, and second, the distribution of firms is highly persistent, i.e. leaders enjoy high productivity over the period of observation and firms at the lower bound of the distribution tend to remain in that position. As a result, β-convergence, driven mainly by new entrants, is not significant enough to translate into aggregate productivity growth, because the share of inefficient stagnating companies in the Russian economy is quite high. The σ-convergence indicator shows no convergence.

We apply stochastic frontier models in order to check whether firms diverge from the frontier despite rapid growth of laggards. In comparison with the σ-convergence model, the stochastic frontier approach is more robust to the choice of leaders and the definition of laggards. According to SFA models, leaders are defined based on performance over the entire sample period. In addition, the convergence parameters are explicitly included in specifications of the production function under this approach. The results of our stochastic frontier analysis confirm that the gap between leaders and laggards widens in most of the industries in our sample. This finding is in line with the results of the analysis of β-convergence*,* where we show that high growth rates peter out as firms age and are unable to maintain their catch-up momentum.

Thus, the results of different convergence analysis methods do not contradict one another. Rather, they reveal the true causes for divergence in firms' productivity levels, which are not the lack of growth at the frontier or low growth of new efficient firms. The true causes are the lack of reallocation of resources from old, inefficient firms to leaders operating at the production frontier or to fast-growing entrants.

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Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's web site:

Supplementary Material

Table A1: List of Industries

Table A2: Results of Dynamic Multinomial Model of Transition Between Productivity Quartiles

Table A3: Estimations Of Productivity Functions According To Battese and Coelli (1992) Specification (Positive γ Means Divergence)

Table A4: Estimations of Productivity Functions According To Modified Kumbhakar (1990) Specification (Positive Year Dummy Means Improvement in Technical Efficiency)