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Productivity Trends in Russian Industries: Firm-Level Evidence

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PRODUCTIVITY TRENDS IN RUSSIAN INDUSTRIES: FIRM-LEVEL EVIDENCE

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ABSTRACT

The paper focuses on convergence of labor and multifactor productivity in Russia. Using firm-level data over 2011-2016 period we obtain the following result: low-productivity firms grow faster, than high-productivity firms. Despite this fact, the initial gap between the most and the least productive firms in the Russian economy is so wide, that it is hardly possible to overcome it in the short run. Moreover we find that this gap has increased during 2011-2016 period, suggesting productivity divergence in Russia. In order to check the divergence hypothesis we also apply stochastic frontier analysis. Our estimates confirm divergence in most industries.

Keywords: productivity, Russia, divergence, stochastic frontier analysis.

JEL Classification: D24, E22, O47.

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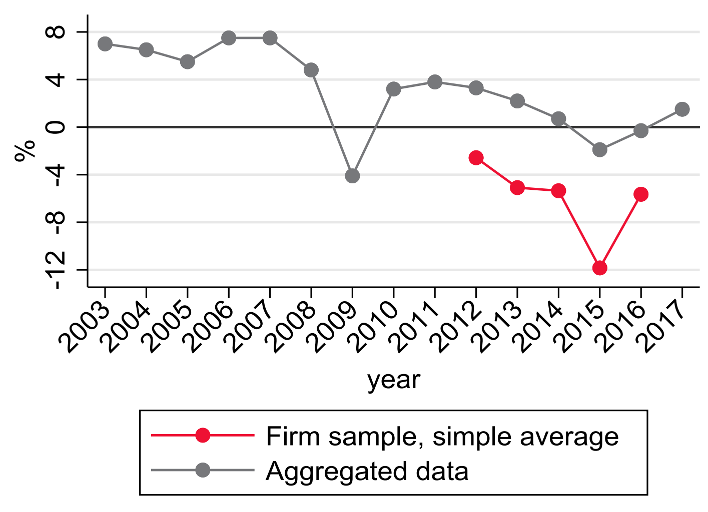
INTRODUCTION

In recent years advanced countries experience slowdown of labor and multifactor productivity (MFP) growth. As in other countries growth slows down in Russia (Figure 1). In 2015 and 2016 growth was negative.

Figure 1. Labor productivity growth in Russia



Source: Rosstat[1]*, Authors' calculations based on Ruslana database*

There are several hypotheses explaining this slowdown:

- Adaptation to new technologies. The diffusion of technologies may take time. In order to exploit all advantages of new technologies firms need to change their business processes and invest in new equipment, training programs for employees. Therefore recently developing technologies will impact productivity growth in future. (Klaus and Xavier, 2016)
- Mismeasurement. Qualitative improvements to products and services, as well as invention of new products, accelerate. These shifts are difficult to calculate since statistics captures only monetary transactions. It is highly possible, that official indicators underestimate productivity gains. As pointed in Aghion et al. (2017) fraction of missing growth in the US economy is sufficient. Nevertheless their estimations indicate slowing productivity growth.
- Innovations are not so drastic now, as they were before. Secular stagnation hypothesis (Gordon, 2015) implies that productivity growth slows down since

[1]Labor productivity indices in the economy of the Russian Federation:
http://www.gks.ru/free_doc/new_site/vvp/vvp-god/ipt-okved2.xlsx
http://www.gks.ru/free_doc/new_site/vvp/vvp-god/pr-tru.xlsx

technical progress is not as intensive as it was earlier. Today's innovations are less influential compared to invention of steam engine or electric light.

Increasing inequality. According to opposite hypothesis, the growth at the frontier remains high. The reason for aggregate slowdown of productivity growth is change in performance of non-frontier firms due to decline in knowledge diffusion (Andrews et al., 2016; Akcigit and Ates, 2019).Availability of firm-level data gives an opportunity to examine these hypotheses, what lies behind aggregate indicator changes. The secular stagnation hypothesis implies that productivity growth slows down due to slowdown in technical progress. It means that the most productive firms (firms at the frontier) do not grow as fast as they did before. The opposite hypothesis implies that the gap between the leaders and laggards increases.

A host of literature finds that the productivity is highly heterogeneous even in narrowly defined industries. In several papers convergence is assumed, because low productive firms grow faster than high productive firms (see Griffith et al. (2009), Bournakis and Mallick (2018), Gemmel et al. (2016), Brown et al. (2015), Conway et al. (2015), Chevalier et al. (2012)).

Andrews et al. (2016) and Cette et al. (2018) confirm this result. However they show that the evolution of the gap between leaders and laggards depends on the definition of these groups. If leaders are defined as the most productive firms in each year, then the gap between them and laggards increases despite high growth of low-productivity firms.

In line with existing evidence we find, that in a sample of Russian firms productivity growth rates are negatively correlated with initial level of productivity. We also find that the gap between leaders and laggards is much higher than in OECD countries. Moreover, in line with Andrews et al. (2016) and Cette et al. (2018) we find that this gap is growing.

In order to check this result we estimate stochastic frontier model. Our results indicate that the technical efficiency decreases over the sample period. It means that the distance to the frontier (in other words the gap between leaders and laggards) increases. Therefore we confirm that fast growth of low productive firms doesn't lead to convergence.

The remainder of the paper is organized as follows. Section 2 summarizes the results obtained in related literature. In section 3 we describe the data on Russian firms. In section 4 we analyze productivity convergence from two points of view: firstly, the correlation between initial level of productivity and its growth; secondly the dispersion analysis. In section 5 we provide our robustness check for the main conclusion that the gap between leaders and laggards increases. Section 6 concludes.

1. RELATED LITERATURE

Series of studies is focused on the factors influencing the productivity growth. Existing literature suggests that initial level of productivity is negatively correlated with its growth (Griffith et al., 2009). Taxation negatively influences the magnitude of this correlation (Gemmel et al., 2016, Bournakis and Mallick, 2018), while openness to foreign markets accelerates catching up (Conway et al. 2015). In these studies the gap between firms with different levels of productivity is left outside the scope of analysis.

The other bulk of literature considers the remarkable variation of productivity as result of resource misallocation. These papers provide the explanation of high productivity dispersion within narrowly defined industries. For example, as Hsieh and Klenow (2009) show aggregate productivity in India and China might be sufficiently improved if the reallocation of resources resulted in productivity dispersion as in the U.S.

In the model of Hsieh and Klenow (2009) the reason for misallocation is two types of distortions, which prevent firms from expanding. The first type is scale distortions. It means that productive firms face barriers if they try to expand, for example size-dependent policy (Guner et al., 2008). The examples of such policies are tax exemptions or direct subsidies for small companies. The second type of distortions leading to misallocation is capital distortions. As Midrigan and Xu (2014) and Gopinath et al. (2017) point out borrowing constraints may prevent productive firms from investing and capital building up.

Bartelsman et al. (2013) argue that scale distortions prevent firms not only from expanding but from entering market as well. Midrigan and Xu (2014) add that borrowing constrains prevent firms from technology adoption and changing their specialization from labor intensive to technology intensive production.

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

Frictions described in this literature influence firms which do not grow although they are productive, but also they impact firms that do not exit although they are low productive. As example Akcigit et al. (2016) compare life cycle of firms in the U.S and in India. In the U.S. if firms are productive they attract resources from less productive firms and grow, while unproductive firms exit the market. Alon et al. (2018) confirm that productivity growth among U.S. young firms is driven by selection and allocation from fast exiting nonproductive firms to expanding high-productivity firms. In India there is little distinction between productive and unproductive firms. Productive firms face barriers preventing them from growth and stay small. They don’t weed out unproductive firms, which have opportunity to survive. As consequence, there are not enough successful and productive companies in India and the gap between leaders and laggards remains high.

Andrews et al. (2016) suggest that one of the forms of resource misallocation may be slow technology diffusion. Therefore firms face the lack of access to tacit knowledge and opportunities to grow. In other words, as Midrigan and Xu (2014) point out concerning borrowing constraints, costs for laggards firms of moving from the economy based on production to the economy based on ideas increases.

Andrews et al. (2016) find that OECD countries also experience the widening gap between leaders and laggards, while the production frontier is still moving forward (at least in services). This suggests that the reason for aggregate productivity slowdown is not technical progress, but the increasing heterogeneity of firms within industries. As Baily and Montalbano (2016) argue, micro analysis finds the explanation of slow growth in weakening in the dynamic adjustments that have traditionally fueled productivity improvement.

Andrews et al. (2016) find that widening productivity gap is accompanied by negative correlation between productivity growth and its initial level. This correlation weakens since 1997. They suggest the following explanation: laggards converge to leaders, but now it takes longer, in other words, convergence slows down.

Cette et al. (2018) also finds that in France low-productivity firms grow faster than high-productivity firms. They present the other argument for convergence: fixed group of firms, which were leaders at the beginning of the sample experiences decline of productivity, while firms which were initially laggards experience productivity growth. But this result is sensitive to the definition of group of leaders. If it is not fixed, and defined as the fraction of the most productive firms in each year, the result is opposite. The gap between leaders and laggards increases since the beginning of 90^{th}.

We follow the approach of Andrews et al. (2016) and Cette et al. (2018). We show that in Russia, as in OECD countries and France low-productivity firms grow faster than high productive firms. However, taking into account new firms and in particular permutation of firms, the dispersion indicators suggest, that firms diverge from the frontier. In order to check this result we apply stochastic frontier analysis. According to this approach leaders are those firms, which are the most productive during the whole period. We use two different specifications, which both confirm that in most industries firms diverge from the frontier.

In the next section we describe data we use to estimate convergence patterns in Russian firms.

2. DATA

Firm level data come from Bureau van Dijk's Ruslana database. It contains information on companies in Russia, Ukraine and Kazakhstan. In particular, it provides their financials over the past 10 years. The advantage of Ruslana database over similar database SPARK-INTERFAX is availability of employment data. Until recently the data concerning employees was presented in SPARK as broad categories instead of precise number. It makes the productivity estimation impossible.

We use data from 2011 to 2016 on operating revenue, fixed assets, employment, cost of goods sold, labor cost, and date of incorporation. As discussed in OECD (2001) Measuring Productivity Manual, revenue as well as value added may be considered as measure of output. We use value added following Aigner and Chu (1968), Greene (1980), Petrin and Levinsohn (2012), Andrews et al. (2016), Cette et al. (2018), because it is consistent with economy-wide productivity measures. We construct value added as revenue less cost of goods sold plus labor cost. It made our sample sufficiently less, because the data on labor cost is represented worse, than other financials. In case of value-added concept of productivity only primary inputs are used as firms' inputs, materials are not taken into account.

In order to calculate the official productivity index Rosstat use hours worked as approximation of labor input. As we do not have data on hours worked, we use employment as approximation for labor following Aigner and Chu (1968), Greene (1980), Andrews et al. (2016), Cette et al. (2018). We use fixed assets as approximation for capital. Labor productivity is defined as value added divided by employment.

Figure 2. Number of observations by year and sector.

Sector		2011	2012	2013	2014	2015	2016
C	Mining	916	960	1226	1417	1508	1378
D	Manufacturing	9327	9530	12707	14668	15579	16376
E	Utilities	2154	2136	2829	3253	3543	3680
G	Wholesale and retail trade	8930	10755	17417	22544	24207	25633
H	Hotels and restaurants	973	978	1479	1706	1875	1873
I	Transportation and communications	3172	3384	4635	5405	5820	6109
K	Business services	7531	7980	11412	14457	16262	17705
O	Personal and other services	1606	1556	2407	2671	2671	2707
Total		34609	37279	54112	66121	71465	75461

Source: Ruslana database, authors' calculations

We concentrate our analysis on following sectors: mining and quarrying, manufacturing, utilities, wholesale and retail trade, hotels and restaurants, transportation and communications, business services, personal and other services (see Appendix A). We exclude agriculture, construction, financial services and public sector. Factors used or output produced in these sectors are substantially different from those in our analysis.

Therefore it requires special analysis which takes into account these factors. However in some specifications we use data for agriculture and construction in order to make results comparable with other studies.

We exclude firms with less than 10 employees, because the quality of data. As result, our unbalanced sample is made up of 34609 to 71465 companies per year over 2011-2016 period (Figure 2).

As shown in Figure 3 our sample represents on average 25% of employment according to Rosstat (column 1). At the same time the structure of employment is well reproduced: shares of retail and wholesale trade (sector G) and manufacturing (sector D) are the highest.

Figure 3. Sample representativeness

		Share of employees represented in sample	Number of employees, thousand		Share of sector in total employment, sample	Share of sector in total employment, Rosstat
			Sample	Rosstat		
C	Mining	53%	569	1082	6%	3%
D	Manufacturing	34%	3366	9844	33%	24%
E	Utilities	37%	704	1923	7%	5%
G	Wholesale and retail trade	22%	2808	12890	27%	31%
H	Hotels and restaurants	14%	190	1338	2%	3%
I	Transportation and communications	18%	977	5501	10%	13%
K	Business services	23%	1390	6002	14%	15%
O	Personal and other services	9%	226	2560	2%	6%
Total		25%	10229	41140	100%	100%

Source: Rosstat[2], Ruslana database, authors' calculations.

We divide our sample into 173 industries. We begin with as narrow industry classification as possible. It permits us to assume joint production function for firms in each industry. However, we have to aggregate some industries until we have sufficient number of observations in order to estimate stochastic frontier model. As result the most industries are aggregated at three- or four-digit numerical code of Russian Classification of Economic Activities (OKVED), while some of them aggregated at two-, four-, five- or even six-digit codes (see Appendix B).

Value added and labor productivity are deflated by industry-specific producer price index[3] or by industry specific value added deflator[4]. Capital is deflated by sector specific

[2] Average annual number of employed in Russia by economic activity according to the balance of labor resources
http://www.gks.ru/free_doc/new_site/population/trud/05-05.xls

[3] Producer price indices by economic activity from 2012 to 2016 https://fedstat.ru/indicator/43561

capital price index. It is constructed as value indices[5] divided by volume indices[6]. Volume indices are calculated as growth rates of fixed assets stocks across sectors.

3. PRODUCTIVITY CONVERGENCE

We begin our productivity convergence analysis with study of different productivity patterns among groups of leaders and laggards. Some literature argues that productivity decline in group of leaders and simultaneous growth in group of laggards indicates productivity convergence. We apply two approaches to define labor productivity frontier: division with and without renewal.

Division without renewal approach suggests that group 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 is the least productive firms in 2011 and 10th decile is most productive firms in 2011. Each group is fixed. It means that we assign the group to each company once in 2011. Afterwards firms do not migrate to other group regardless the productivity changes. In other words we follow companies which were in our sample in 2011. This approach is affected by survival bias, because firms exit from the market and we do not include new companies into analysis.

The second approach is division with renewal. According to this approach all firms are included into analysis. In each year we divide our sample into 10 groups, where 1st decile is the least productive, and 10th decile is the most productive group. Firms may migrate from one group to another according to their productivity change. Than we calculate the average productivity in each group and compare it with the result for this group in 2011. Therefore according to this approach it is not important who are members of these groups, instead we focus on the evolution of different moments of productivity distribution.

As shown in literature, according division without renewal leaders' productivity declines while productivity of laggards improves. We calculate average accumulated growth in 1st, 6th, 9h, 10th deciles (Figure 4). The most rapid growth takes place in the group of firms with the lowest labor productivity in 2011. And firms from 10th, 9th and 6th deciles experience decline in labor productivity. This result holds for almost all sectors. This fact may be considered as argument for productivity convergence.

Division with renewal approach yields opposite results: productivity of the most productive firms grows faster than productivity of the less productive firms (Figure 5). The average productivity in most productive deciles improved during the sample period. At the same time the average productivity in the least productive deciles declined. This result holds for all sectors. It means that taking into account the whole sample is extremely

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

[5] Fixed assets at the end of the year at the full book value, full range of organizations, until 2016 https://fedstat.ru/indicator/40442

[6] The physical volume index of fixed assets, full range of organizations, until 2016 https://fedstat.ru/indicator/36733

important. On the one hand, if firms survive despite their low productivity at the beginning of the sample, they grow. The other firms from the least productive group exit. On their place come new low productive firms. They may be entrants or firms with previously higher productivity. In other words, if some firms from the least productive group grow, it doesn't mean that the distribution of all firms converges to the frontier.

Figure 4. Accumulated labor productivity growth, frontier without renewal

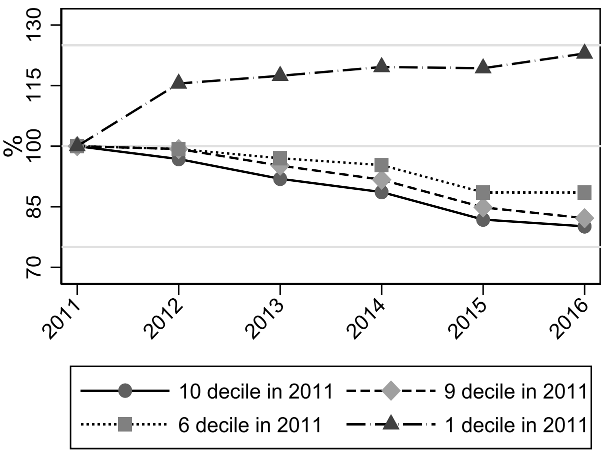
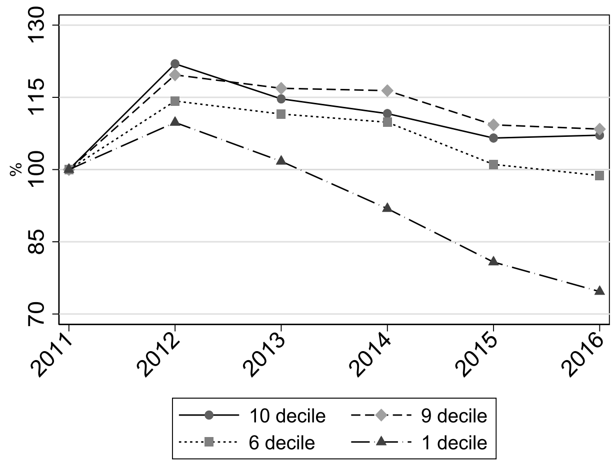


Figure 5. Accumulated labor productivity growth, frontier with renewal



Source: authors' calculations

We proceed with more formal approaches to convergence. Two main concepts of convergence are used in literature.

The first concept is β-convergence. It is said that firms converge when the high initial firm's position is associated with low productivity growth, while low initial position is associated with faster productivity growth. In other words β-convergence means negative correlation between initial level of productivity and its growth.

The second approach is σ-convergence. In this case convergence means that the dispersion of productivity distribution decreases over time. The dispersion indicator is not always dispersion itself. 90 to 10 ratio (the ratio of the 10^{th} decile to the 1^{st} decile of the productivity distribution) or interdecile dispersion (it is calculated as $(10^{th}-1^{st})/(10^{th}+1^{st})$) are also widely used.

β- and σ-convergence approaches may contradict each other. σ-convergence is always accompanied by β-convergence. But the opposite is not always true. Thus, as stated in Young et al. (2008) β-convergence is necessary but not sufficient condition for σ-convergence. The main differences between these two concepts are following:

- β-convergence is estimated over companies which are in the sample for two consecutive years. It means that survival bias impacts the results of β-convergence estimates. Calculation of σ-convergence involves all companies.

- β-convergence is sensitive to permutation. For example, if there only two firms with initially high and low productivity and they exchange their positions, than this approach indicates convergence. Because the low initial level of productivity is associated with growth, while high initial level of productivity is associated with decline. At the same time productivity dispersion is unchanged, the gap between high and low productivity level remains. Therefore dispersion indicates no convergence or divergence.

3.1. β-convergence

Following existing literature we estimate the correlation between initial distance to frontier and productivity growth (β-convergence). We test the hypothesis that laggards grow faster, than leaders.

Average labor productivity growth varies by years, sectors, age and firm size, thus we include these control variables into estimation (Figure 6-Figure 9). In order to control for size we introduce dummy variables: 1) firms with number of employees less than 50, 2) firms with number of employees greater than 50 and less than 250, 3) firms with number of employees greater than 250.

Figure 6. Labor productivity growth by years

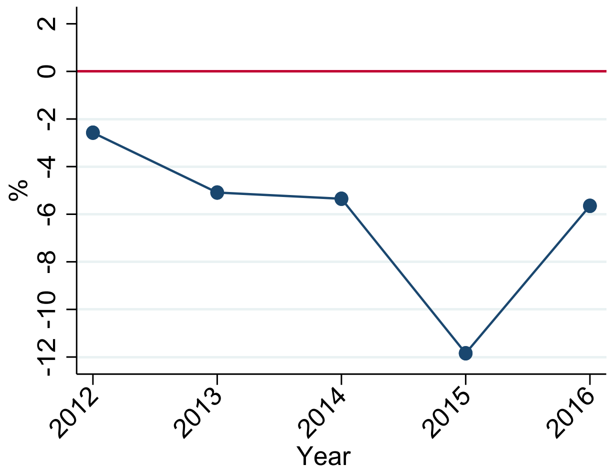


Figure 7. Labor productivity growth by sectors

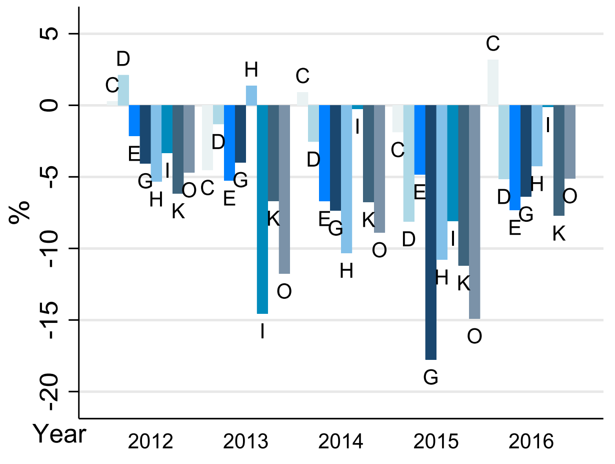
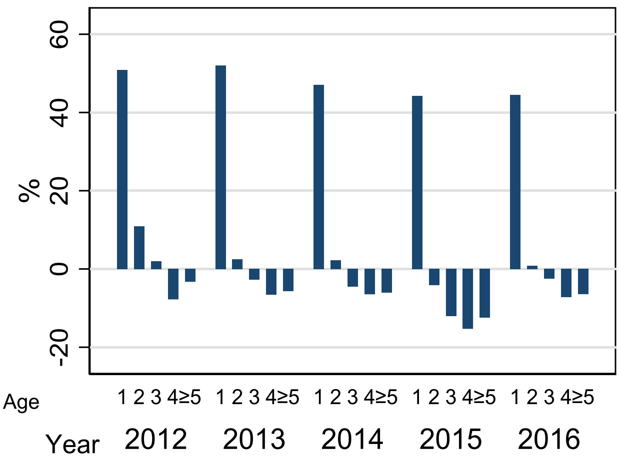
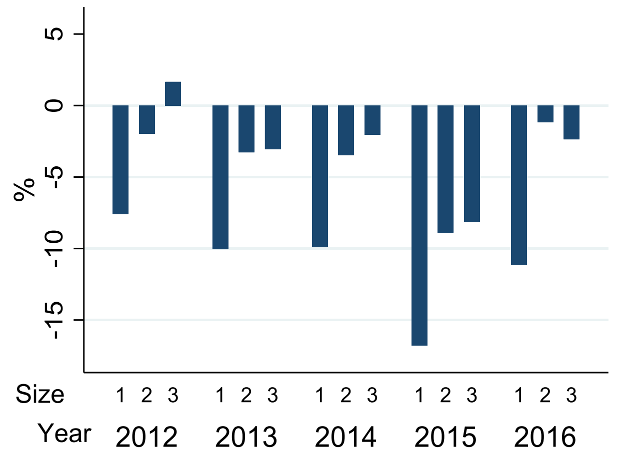


Figure 8. Labor productivity growth by age

Figure 9. Labor productivity growth by size





Source: authors' calculations

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At the first step we estimate the following equation with controls for size, age, sector and year (model 1).

$$\Delta lp_{it} = \beta_0 + \beta_1 gap_{it-1} + \beta_3 age_{it} + \beta_4 age_{it}{}^2 + \sum_{p=2}^{3} \beta_p * G_p + \sum_{j=2013}^{2016} \beta_j * Y_j + \sum_{k=2}^{8} \beta_k * S_k,$$

where

Δlp_{it} – growth rate of labor productivity of firm i, Δlp_{it} is calculated as difference of log labor productivity in year t and year $t-1$;

age_{it} – age of firm i in period t; we also include squared age in order to control for possible nonlinear relation between age and labor productivity growth;

G_p – dummy variable for pth size;

Y_j – dummy variable for jth year;

S_k – dummy variable for kth sector,

gap_{it} – difference between the median of the productivity of 5% most productive firms and the productivity of firm i in year t (distance to the frontier).

Significant positive coefficient for the distance to frontier (Table 1) implies that the better initial conditions, the lower the labor productivity growth rate in line with Cette et al. (2018) and Andrews et al. (2016). It suggests β-convergence.

Next we allow the speed of convergence to differ across years and sectors as we include interactions of these dummies with the distance to frontier (model 2):

$$\Delta lp_{it} = \beta_0 + \beta_1 gap_{it-1} + \beta_2 age_{it} + \beta_3 age_{it}{}^2 + \sum_{p=2}^{3} \beta_p * G_p + \sum_{j=2013}^{2016} \beta_j * Y_j + \sum_{k=2}^{8} \beta_k * S_k$$
$$+ \sum_{l=2013}^{2016} \beta_l * Y_l * gap_{it-1} + \sum_{m=2}^{8} \beta_m * S_m * gap_{it-1},$$

where Y_l – dummy variable for lth year;

S_m – dummy variable m-th sector.

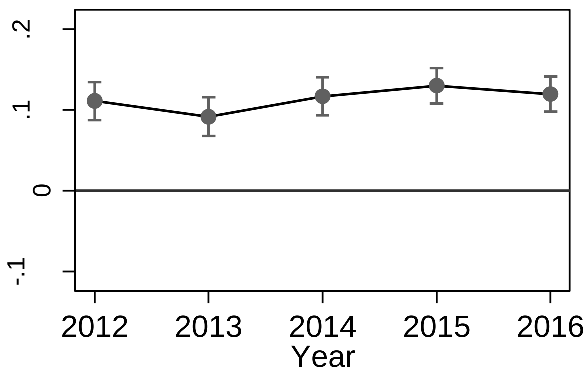
We find β-convergence in all year and almost in all sectors in our sample (Figure 6 and Figure 7).

For robustness checks we estimate other specifications following Cette et al. (2018) (model 3) and Andrews et al. (2016) (model 4) (Table 1). Instead of labor productivity we calculate multifactor productivity (MFP). And test the same hypothesis for this indicator of productivity: whether the laggards grow faster than leaders.

In both models MFP is calculated as the ratio of the value added to geometric average of two factors labor and capital. The weights of factors are calculated differently in two models.

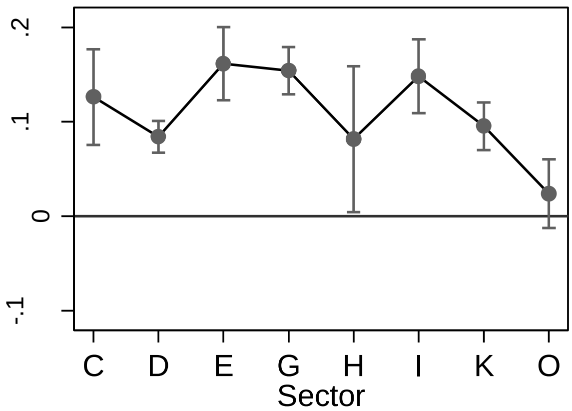
In the third model we estimate the weights using non-parametric approach. We calculate the weight of labor as mean share of labor costs in value added by industry. We estimate the weight of the capital as residual, assuming constant returns of scale. In model 3 we include sectors according to the choice made by Cette et al., 2018. The frontier firms are defined as the top 5% in sector rather than in industry.

Figure 10. Speed of β-convergence by years



Source: authors' calculations

Figure 11. Speed of β-convergence by sectors



Source: authors' calculations

In the fourth model we estimate labor and capital shares as elasticities of the value added with respect to labor and capital. In order to estimate production functions we use Levinsohn-Petrin-Wooldridge approach. We include growth rate at the frontier into regression in model 4. The choice of sectors is made according Andrews et al. (2016). The errors are clustered at industry level.

In model 3 size and sector dummies are constructed as in our baseline models 1 and 2. In model 4 firm size and age captured by a set of fixed effects, corresponding to the following categories in employment: below 50, 50-99, 100-250, 25-999, 1000 and above; and in age: 0-2, 3-4, 5-9, 10-29, 30 and older.

The difference between the models 5, 6 and 7 and the models 2, 3, 4 is that we use fixed effects estimation instead of pooled regression. In fixed effects models the speed of β-convergence is higher than in pooled, because during periods when the company is further away from the frontier than on average, the growth is higher in order to reach average distance to frontier.

Table 1. Estimation results of simple β-convergence

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Productivity	Labor productivity	Labor productivity	MFP	MFP	Labor productivity	MFP	MFP
MFP estimation	-	-	Non-parametric: share of laborcost in value added	Levinsohn-Petrin-Wooldridge	-	Non-parametric: share of laborcost in value added	Levinsohn-Petrin-Wooldridge
Frontier identification	5% best in industry	5% best in industry	5% best in sector	5% best in industry	5% best in industry	5% best in sector	5% best in industry
Sectors	C D E G H I K O	C D E G H I K O	A C D E F G I O	C D E F G H I K	C D E G H I K O	A C D E F G I O	C D E F G H I K
Regression	Pooled	Pooled	Pooled	Pooled	Fixed effect	Fixed effect	Fixed effect
Error clusterisation	No	No	No	Yes	No	No	Yes
Coefficient of convergence	**0.033974**	**0.0540827**	**0.0382778**	**0.0851951**	**0.4834539**	**0.6136459**	**0.6507607**
Frontier growth	No	No	No	Yes	No	No	Yes
Age controls	Yes	Yes	No	Yes	Yes	No	Yes
Size dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	No	No	No
Year*gap interaction	No	Yes	Yes	Yes	Yes	Yes	Yes
Sector*gap interaction	No	Yes	No	No	No	No	No

Note: all estimated convergence coefficients are significant at 1% level.

3.2. σ-convergence

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

Berlingieri et al. (2017) report σ-divergence of productivity based on firm-level data from OECD countries. As the main indicator of dispersion they use the difference between the 90th and 10th percentiles of log-productivity (90 to 10 ratio). This indicator takes into account change of the sample over time and all shocks, which are neglected by β-convergence indicator. On the other hand the extreme observations with the highest and the lowest productivity are excluded from the analysis. It makes 90 to 10 ratio more robust to outliers, than the simple standard deviation.

We start with the first indicator of the productivity dispersion: the ratio of the 10th decile to the 1st decile of the productivity distribution (90 to 10 ratio). Berlingieri et al. (2017) calculate this ratio for manufacturing and services for 16 countries[7] in 2011.

Figure 12. Ratio of labor productivity of the 10th decile to the 1st decile, division without renewal, logarithmic scale

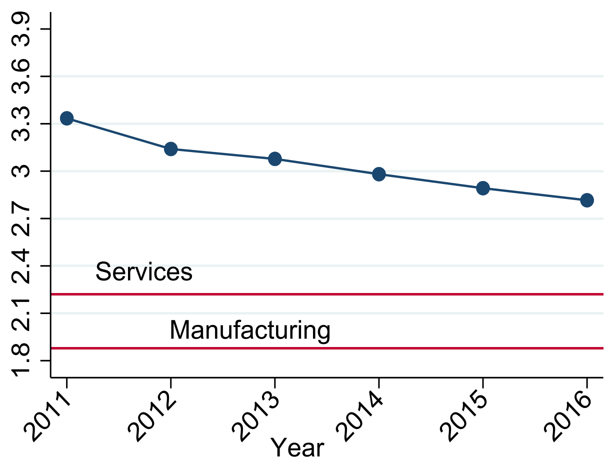
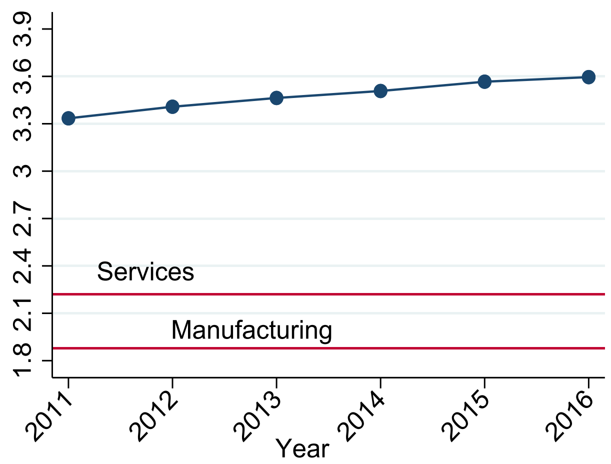


Figure 13. Ratio of labor productivity of the 10th decile to the 1st decile, division with renewal, logarithmic scale



Source: authors' calculations

Figure 12 shows that in 2011 the log of the ratio was 3.48. Red lines correspond to unweighted averages by countries calculated by Berlingieri et al. (2017). We find that in Russia the ratio was higher than in all countries in the sample presented by Berlingieri et al. (2017), except services sector in Chile. The estimates for US are also lower: 1.9 in 1997-2010 reported by Cunningham et al. (2017) and 1.4 in 1977 reported by Syverson (2004). Relatively high level of productivity dispersion may be associated with high regional inequality in Russia.

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

Applying division without renewal approach we find that the ratio declined during sample period. It means that among firms which were in the sample in 2011 the gap decreased. But it remained higher, than the values reported by Berlingieri et al. (2017). Wholesale and retail trade (G) and business services (K) are characterized by the greatest gap between the most and the least productive firms.

If we focus on 1st and 10th deciles in each year, including all firms into our analysis, we find that the gap remains substantially higher than Berlingieri et al. (2017) present. Moreover during the sample period the ratio increased.

Figure 14 summarizes the difference between productivity 90 to 10 ratio in 2016 and in 2011 across 173 industries in the sample. Unlike Griffith et al. (2009) or Conway et al. (2015) we find, that in the most industries the dispersion increased during the sample period. Mining and quarrying (sector C) experienced the highest growth of the ratio. This suggests that mining and quarrying experienced the most rapid divergence of labor productivity.

Figure 14. Change of the 90 to 10 ratio of labor productivity in 173 industries in 2011-2016

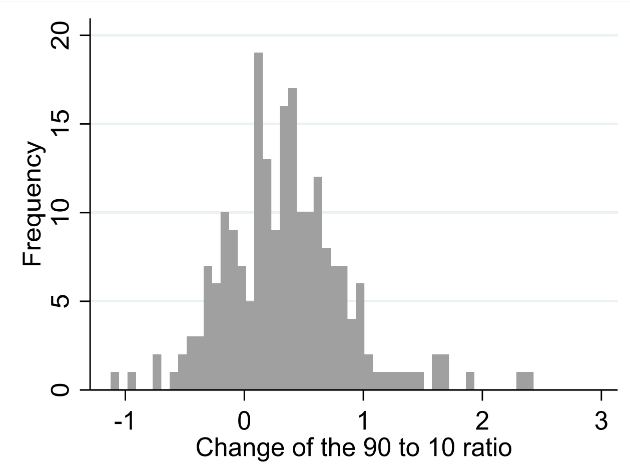
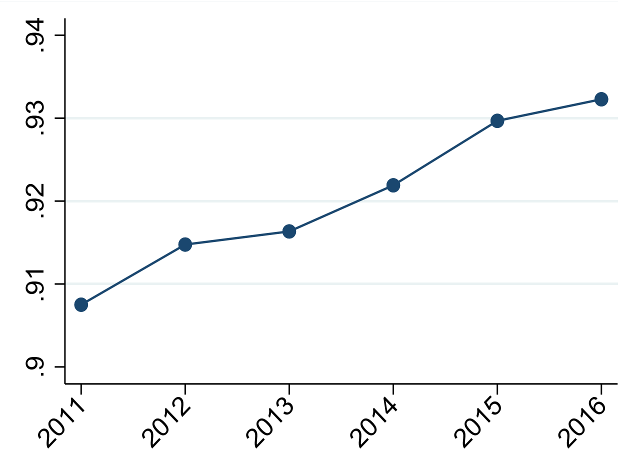


Figure 15. Interdecile dispersion of labor productivity (10th-1st)/(10th+1st)



Source: authors' calculations

The other indicator of σ-convergence is interdecile dispersion. It is calculated as the difference between the 10th and the 1st decile divided by their sum. As Figure 15 shows this indicator grows during the sample period. Cette et al. (2018) obtained the same result for French companies. Thus both indicators give evidence for σ-divergence.

Another argument for slow convergence is shown in Figure 16. Transition matrices between quartiles illustrates that the group of the most productive firms are relatively stable. For example, 78% of most productive firms (4th quartile) in 2011 remain in the same quartile, 19% of them go down to 3rd quartile, 2% to 3rd quartile and 1% to the worst quartile. After 2011 year the share of the most productive firms remaining in the 4th quartile is even higher 84-86%. Moreover, the share of firms from 3rd quartile improving to the 4th quartile is no more than 15%.

Using labor productivity data we show that laggards grow faster than leaders as Figure 4 shows. Moreover we find significant β-convergence coefficient. But the starting point of the least productive firms is very low. During 6 years of the sample period firms which were the least productive in 2011 approached leaders, but they remain far less productive. The gap between the most and the least productive firms is too wide to overcome in in the nearest future. Moreover despite β-convergence we find that taking into account all firms, including new in the sample, the gap between the most and the least productive firms increases.

Figure 16. Transition matrices between quartiles of labor productivity distribution

		2012				
		4	3	2	1	
2011	4	77%	20%	2%	1%	100%
	3	8%	64%	24%	3%	100%
	2	1%	11%	67%	21%	100%
	1	1%	2%	11%	86%	100%

		2013				
		4	3	2	1	
2012	4	85%	13%	2%	1%	100%
	3	15%	66%	16%	3%	100%
	2	2%	17%	67%	14%	100%
	1	1%	2%	16%	81%	100%

		2014				
		4	3	2	1	
2013	4	85%	13%	2%	1%	100%
	3	14%	67%	17%	2%	100%
	2	2%	16%	67%	15%	100%
	1	1%	2%	16%	81%	100%

		2015				
		4	3	2	1	
2014	4	84%	14%	2%	1%	100%
	3	14%	66%	17%	3%	100%
	2	2%	17%	66%	15%	100%
	1	1%	3%	16%	80%	100%

		2016				
		4	3	2	1	
2015	4	84%	13%	2%	1%	100%
	3	14%	67%	17%	3%	100%
	2	2%	16%	66%	16%	100%
	1	1%	2%	15%	82%	100%

Source: authors' calculations

In the next section we proceed with stochastic frontier analysis. According to this approach groups of leaders and laggards are defined based on the firms' performance during the whole period. It makes this type of models more robust to the way how leaders defined: as fixed group in the first year of the sample (division without renewal) or the group of leaders is redefined each year (division with renewal). Applying stochastic frontier model we check the hypothesis that despite β-convergence the gap between leaders and laggards increases.

4. MULTIFACTOR PRODUCTIVITY CONVERGENCE UNDER STOCHASTIC FRONTIER MODEL

In order to check the result obtained in the previous section we apply stochastic frontier models. This approach doesn't allow us to estimate the level of productivity, but it allows us to estimate multifactor productivity growth as well as relative efficiency and its evolution simultaneously, because convergence parameters are explicitly included into specifications. This model is insensitive to the way of how leaders are defined, because performance during the whole sample period is taken into account.

4.1. Methodology

We adopt panel production frontier model with translog specification (see, for example, Kim, 1992; Coelli et al., 1999; Coelli et al., 2003; Adetutu et al., 2015):

$$y_{it} = \beta_0 + \beta_1 l_{it} + \beta_2 k_{it} + \beta_3 t + \beta_4 l_{it}^2 + \beta_5 k_{it}^2 + \beta_6 t^2 + \beta_7 l_{it} k_{it} + \beta_8 l_{it} t + \beta_{89} k_{it} t + v_{it} - u_{it},$$

where

y_{it} is logarithm of value added of firm i in period t,

l_{it} - logarithm of labor force,

k_{it}– logarithm of capital used,

t – period of time,

v_{it} – error term, $v_{it} \sim N(0, \sigma_v^2)$,

$u_{it} \geq 0$ represents technical inefficiency.

Deterministic part of production function represents production frontier, i.e. maximum level of production at given levels of labor and capital.

For the inefficiency part we adopt two types of specifications:

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 – time invariant component of inefficiency,

$u_i \sim N^+(0, \sigma_u^2)$, $G(t)$ – time function,

γ – the decay parameter,

T – terminal period.

γ – the parameter, indicating convergence or divergence. If $\gamma < 0$ firms converge to frontier, and if $\gamma > 0$ firms diverge from the frontier. The model ignores temporary productivity deviations. It smooths fluctuations of productivity, consequently only firms with constantly high productivity levels are regarded as leaders. Since by definition the groups of leaders is stable during the sample period, time decay specification compromises between two approaches of frontier defining (division with or without renewal).

2. the modified Kumbhakar (1990) model:

$$u_{it} = G(t)u_i,\ G(t) = \left[1 + \exp\left(\sum_{p=2}^{3} \beta_p * G_p + \sum_{j=2013}^{2016} \beta_j * Y_j\right)\right]^{-1},$$

Where

u_i – time invariant component of inefficiency, $u_i \sim N^+(0, \sigma_u^2)$,

$\mathrm{G(t)}$ – time function, G_p – dummy variable for pth size; Y_j – dummy variable for jth year.

The crucial difference between two specifications is that the second specification is more flexible. It allows for inefficiency fluctuations during the sample period, while under the first specification no deviation from trend is assumed.

We estimate the time varying decay specification for all 173 industries in our sample. In order to estimate the second specification Kumbhakar 90 we exclude two industries.

Both specifications enable us to estimate technical efficiency index, i.e. distance to the frontier: $Index = \exp\left(u_{it}\right)$. Its value lies between 0 and 1. It is another measure of firm efficiency along with relative labor productivity, estimated in previous section.

Multifactor productivity (MFP) growth may be calculated as a sum of three components (see Kumbhakar and Lovell, 2000):

$$M\dot{F}P = T\Delta + TE\Delta + (\varepsilon - 1)\left(\frac{\varepsilon_k}{\varepsilon}\frac{dk}{dt} + \frac{\varepsilon_l}{\varepsilon}\frac{dl}{dt}\right).$$

The first component $T\Delta$ corresponds to technical progress. It is calculated as $T\Delta = \frac{dy}{dt}$. Thus this component reflects shifts in production frontier. Positive technical progress component means that the potential output at given level of resources increases. And vice versa, negative technical progress means that the maximum possible output decreases.

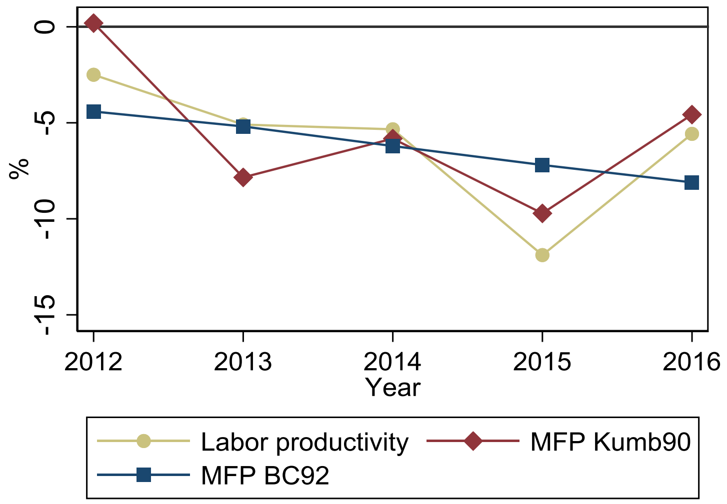
The second component $TE\Delta$ corresponds to technical efficiency change. It is calculated as $TE\Delta = -\frac{du_{it}}{dt}$. This component reflects shifts relatively to the frontier. Positive technical efficiency means that that the firm improves its efficiency, technical efficiency index increases and distance to frontier decreases. As consequence positive technical efficiency component implies convergence to the frontier, while negative technical efficiency component implies divergence from the frontier.

The last component in the decomposition presents allocative effect. It reflects MFP growth thanks to reallocation of resources. Increasing returns to scale implies that output increases by a larger proportion than the increase in resources. In this case the attraction of more inputs is reasonable and this contributes to positive MFP changes. If in this case a firm is forced to reduce its use of inputs the allocative effects would be negative.

4.2. Multifactor productivity trends

The estimated MFP growth rates are relatively close to labor productivity growth rates (Figure 17). But according to the time varying decay specification MFP growth rate are smoothed, in particular there is no improvement in 2016 as other measures indicate.

Figure 17. Different productivity growth estimations



Despite the similarity between estimated MFP growth rates and labor productivity growth rate, the evolution of efficiency according two methods are different. The group of frontier firms in stochastic productivity model is more stable, than group of labor productivity leaders in previous section.

In order to illustrate the difference between two methods we calculate transition matrices between quartiles of technical efficiency distribution for the time decay specification. The results for the Kumbhakar 90 specification are almost the same.

Figure 18 shows, that these groups are even more stable, than quartiles of labor productivity distribution. It is almost impossible to improve from the 3rd to the 4th quartile of estimated technical efficiency.

Figure 18. Transition matrices between technical efficiency quartiles

		2012				
		4	3	2	1	
2011	4	86%	14%	0%	0%	100%
	3	0%	84%	16%	0%	100%
	2	0%	0%	86%	13%	100%
	1	0%	0%	1%	99%	100%

		2013				
		4	3	2	1	
2012	4	94%	6%	0%	0%	100%
	3	3%	90%	7%	0%	100%
	2	0%	2%	91%	7%	100%
	1	0%	0%	2%	98%	100%

		2014				
		4	3	2	1	
2013	4	95%	5%	0%	0%	100%
	3	2%	91%	7%	0%	100%
	2	0%	2%	92%	6%	100%
	1	0%	0%	2%	98%	100%

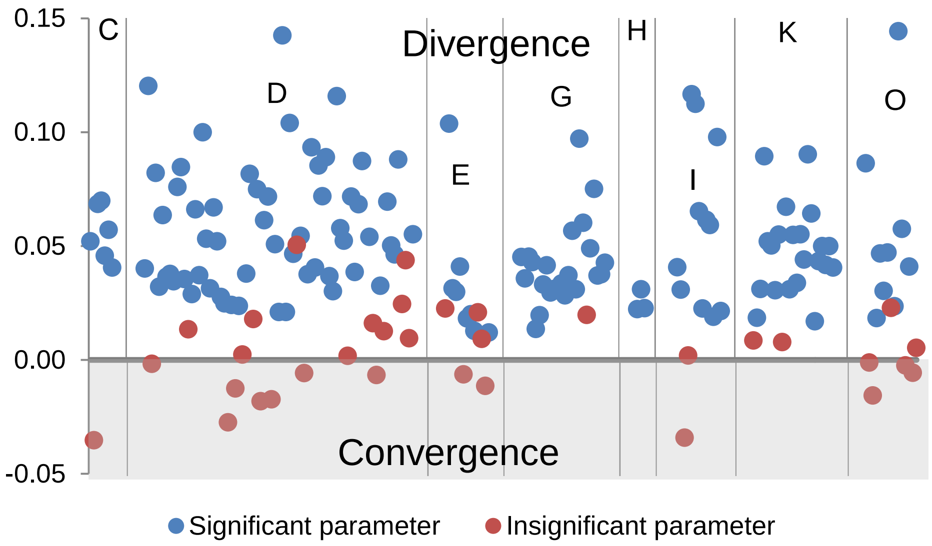
		2015				
		4	3	2	1	
2014	4	96%	4%	0%	0%	100%
	3	1%	93%	6%	0%	100%
	2	0%	2%	94%	5%	100%
	1	0%	0%	2%	98%	100%

		2016				
		4	3	2	1	
2015	4	95%	5%	0%	0%	100%
	3	1%	92%	7%	0%	100%
	2	0%	1%	93%	6%	100%
	1	0%	0%	1%	99%	100%

4.3. **Multifactor productivity convergence**

We apply results of stochastic frontier model estimation in order to analyze converge of MFP. In the time varying decay model γ – convergence parameter. Positive γ indicates divergence and negative γ indicates convergence. In most industries in our sample we find positive γ. It means that technical efficiency worsened during the sample period, companies diverge from the frontier. As Figure 19 shows among 173 industries under investigation we find 139 industries with statistically significant decay parameter. In all these industries we estimate positive decay parameter. It indicates that firms diverge from the frontier. In the rest of the industries we fin insignificant parameter γ suggesting no evidence for convergence.

Figure 19. Estimated convergence parameters of the time varying decay model by industries



Source: authors' calculations

We compare the performance of the industries, in which firms do not diverge from the frontier, to industries, where divergence is found. In order to do so we analyze broader industries, than in our main analysis. They include both industries where firms diverge from the frontier and industries, where firms do not diverge from it. As result we focus on 22 industries, 18 of them are aggregated at two-digit level of OKVED, 3 of them are aggregated at four-digit level of OKVED and 1 industry is aggregated at three-digit level of OKVED.

We find that in most industries absence of divergence is associated with lower technical progress change ($T\Delta$). It means that productivity evolution of firms in these industries is homogeneous. But it is lower than productivity growth of leaders in industries, where most firms diverge from the frontier. Thus absence of divergence doesn't lead to higher resulting productivity growth. In diverging industries aggregate productivity growth may be higher due to better performance of leaders.

In Mining and quarrying sector (sector C) we do not find divergence only in mining and agglomeration of lignite and peat. Among 75 industries in Manufacturing (sector D) in our sample we find no evidence for divergence in 17. They include one food industry, one textile industry, manufacture of refined petroleum products, manufacture of rubber products, three industries producing non-metallic mineral products, manufacture of tubes, two metal products industries, three industries producing machinery, electrical and electronic equipment, manufacture of motor vehicles, three industries producing other products.

Firms in more than one third of Utility industries (sector E) do not diverge from the frontier. They include two industries producing electricity and three industries producing steam and hot water. We find only one industry in Wholesale and retail trade (sector G), where firm firms do not diverge from the frontier. It is Retail sale of electrical household appliances and radio and television goods.

We do not find evidence for convergence in two industries in Transport, storage and communication (sector I). They are transport via pipelines and sea and coastal water transport. Among industries in Real estate, renting and business activities (Sector K) firms do not diver from the frontier in real estate activities with own property and in data processing.

In Other community, social and personal service activities (Sector O) we do not find evidence for divergence in six industries. They include two industries operating in waste collection, News agency activities and three industries operating in personal services.

The results of Kumbhakar 90 specification suggest that in most of the industries the bigger size is associated with the higher technical efficiency (97 industries out of 171). Only in 6 industries transition from the first size class to the second improves the technical efficiency. In the rest of the industries (68 industries) we do not find this association.

As in the time varying decay model Kumbhakar 90 estimations indicate that in the most of the industries technical efficiency worsened during the sample period. In 95 industries out of 171 we find negative coefficient for the 2016 dummy variable. It means that the technical efficiency in 2016 is lower than in 2011, i.e. the distance to the frontier is greater. Only in 10 industries the technical efficiency improves from 2011 to 2016. In the rest 66 industries the change in technical efficiency is not significant.

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

5. CONCLUSIONS

In almost all studies concerning the correlation between productivity level and its growth β-convergence is found. It means that 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 fast growth of laggards relatively to other groups of firms doesn't lead to the decreasing gap. Instead σ-convergence is found, i.e. increasing dispersion of productivity.

We show that this result also holds for Russian firms. Despite β-convergence, the distance between leaders and laggards is sufficiently larger than reported for other countries. It continues to grow suggesting divergence.

The β-convergence model takes into account only those firms, which were in the sample for two consecutive years. On the contrary σ-convergence model takes into account all firms in the sample, but ignoring the panel structure of the data. In other words sample is split into subsamples which are treated separately.

In order to check the divergence result we apply stochastic frontier. This approach is more robust to the choice of leaders and laggards definition. According to SFA models leaders are defined based on firms' performance during the whole sample period. The other advantage of this method is the fact that we can estimate efficiency and its evolution simultaneously, because converge parameter is explicitly included into the specification of production function.

The results of our stochastic frontier analysis confirm that in the most industries in our sample the gap between leaders and laggards increases. In other words, despite the high productivity growth of laggards the dispersion of productivity levels raises.

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Appendix A

Sector list

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

Appendix B

Industry list

Sector code	Industry code	Industry
C	10.1 †	Mining and agglomeration of hard coal
C	10.2+10.3 § ‡	Mining and agglomeration of lignite and peat
C	11.1	Extraction of crude petroleum and natural gas
C	11.2	Service activities incidental to oil and gas extraction, excluding surveying
C	13	Mining of metal ores
C	14.1	Quarrying of stone
C	14.2 †	Quarrying of sand and clay
D	15.1	Production, processing and preserving of meat and meat products
D	15.2 †	Processing and preserving of fish and fish products
D	15.3 § †	Processing and preserving of fruit and vegetables
D	15.4	Manufacture of vegetable and animal oils and fats
D	15.5	Manufacture of dairy products
D	15.6	Manufacture of grain mill products, starches and starch products
D	15.7 †	Manufacture of prepared animal feeds
D	15.8	Manufacture of other food products
D	15.9 †	Manufacture of beverages
D	17.1+17.2	Preparation and spinning of textile fibres and Textile weaving
D	17.4	Manufacture of made-up textile articles, except apparel
D	17.5	Manufacture of other textiles
D	17.6+17.7 § ‡	Manufacture of knitted and crocheted fabrics and articles
D	18	Manufacture of wearing apparel: dressing and dyeing of fur
D	19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear
D	20.1 †	Sawmilling and planing of wood; impregnation of wood
D	20.2	Manufacture of veneer sheets; manufacture of plywood, laminboard, particle board, fibre board and other panels and boards
D	20.3 †	Manufacture of builders' carpentry and joinery
D	20.4+20.5 †	Manufacture of wooden containers and other products of wood; manufacture of articles of cork, straw and plaiting materials
D	21.1	Manufacture of pulp, paper and paperboard
D	21.2	Manufacture of articles of paper and paperboard
D	22.1	Publishing
D	22.2 †	Printing and service activities related to printing
D	23.2 § ‡	Manufacture of refined petroleum products
D	24 †	Manufacture of chemicals and chemical products
D	25.1 § ‡	Manufacture of rubber products
D	25.2	Manufacture of plastic products
D	26.1 § ‡	Manufacture of glass and glass products
D	26.2+26.32 †	Manufacture of non-refractory ceramic goods other than for construction purposes; manufacture of refractory ceramic products and ceramic tiles and flags
D	26.4	Manufacture of bricks, tiles and construction products, in baked clay
D	26.5 § †	Manufacture of cement, lime and plaster
D	26.6 ~	Manufacture of articles of concrete, plaster and cement
D	26.7 § ‡	Cutting, shaping and finishing of stone
D	26.8	Manufacture of other non-metallic mineral products
D	27.1 †	Manufacture of basic iron and steel and of ferro-alloys

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Sector code	Industry code	Industry
D	27.2 § †	Manufacture of tubes
D	27.3 †	Other first processing of iron and steel and production of ferro-alloys
D	27.4 †	Manufacture of basic precious and non-ferrous metals
D	27.5	Casting of metals
D	28.1 †	Manufacture of structural metal products
D	28.2	Manufacture of tanks, reservoirs and containers of metal; manufacture of central heating radiators and boilers
D	28.3 †	Manufacture of steam generators, except central heating hot water boilers
D	28.4 §	Forging, pressing, stamping and roll forming of metal; powder metallurgy
D	28.5	Treatment and coating of metals; general mechanical engineering
D	28.6 § ‡	Manufacture of cutlery, tools and general hardware
D	28.7	Manufacture of other fabricated metal products
D	29.11	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines
D	29.12 †	Manufacture of pumps and compressors
D	29.13 †	Manufacture of taps and valves
D	29.21	Manufacture of furnaces and furnace burners
D	29.22	Manufacture of lifting and handling equipment
D	29.23 †	Manufacture of non-domestic cooling and ventilation equipment
D	29.24 †	Manufacture of other general purpose machinery n.e.c.
D	29.3	Manufacture of agricultural and forestry machinery
D	29.4 ~	Manufacture of machine-tools
D	29.5	Manufacture of other special purpose machinery
D	29.7 § †	Manufacture of domestic appliances n.e.c.
D	30.0	Manufacture of office machinery and computers
D	31.1	Manufacture of electric motors, generators and transformers
D	31.2	Manufacture of electricity distribution and control apparatus
D	31.3	Manufacture of insulated wire and cable
D	31.4 †	Manufacture of accumulators, primary cells and primary batteries
D	31.5	Manufacture of lighting equipment and electric lamps
D	31.6 §	Manufacture of electrical equipment n .e .c.
D	32 § †	Manufacture of radio, television and communication equipment and apparatus
D	33	Manufacture of medical, precision and optical instruments, watches and clocks
D	34.1 § †	Manufacture of motor vehicles
D	34.2	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers
D	34.3	Manufacture of parts and accessories for motor vehicles and their engines
D	35.2 †	Manufacture of railway and tramway locomotives and rolling stock
D	36.1	Manufacture of furniture
D	36.2 § †	Manufacture of jewellery and related articles
D	36.5 § †	Manufacture of games and toys
D	36.6 § †	Miscellaneous manufacturing n.e.c.
D	37.1 †	Recycling of metal waste and scrap
E	40.11.1 § †	Production of electricity by thermal stations
E	40.11.5	Power pant supposrtung activities
E	40.12 †	Transmission of electricity
E	40.13.1	Operation of distribution systems
E	40.13.2	Sale of electricity to the user
E	40.13.3 § †	Distribution electricity supporting activities
E	40.2	Manufacture of gas; distribution of gaseous fuels through mains
E	40.30.0 †	Steam and hot water supply
E	40.30.1 ‡	Production of steam and hot water for heating, power and other purposes

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Sector code	Industry code	Industry

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Sector code	Industry code	Industry
E	40.30.2 § †	Collection of steam and hot water for heating, power and other purposes
E	40.30.3 § ‡	Distribution of steam and hot water for heating, power and other purposes
E	40.30.4+40.30.5 § †	Production and distribution of steam amd hot water supporting activities and Sale of of steam and hot water
E	41.0	Collection, purification and distribution of water
G	50.1	Sale of motor vehicles
G	50.2	Maintenance and repair of motor vehicles
G	50.3	Sale of motor vehicle parts and accessories
G	50.5	Retail sale of automotive fuel
G	51.1 †	Wholesale on a fee or contract basis
G	51.2 †	Wholesale of agricultural raw materials and live animals
G	51.3	Wholesale of food, beverages and tobacco
G	51.4	Wholesale of household goods
G	51.5	Wholesale of non-agricultural intermediate products, waste and scrap
G	51.8	Wholesale of machinery, equipment and supplies
G	51.9	Other wholesale
G	52.1	Retail sale in non-specialized stores
G	52.2	Retail sale of food, beverages and tobacco in specialized stores
G	52.3	Retail sale of pharmaceutical and medical goods, cosmetic and toilet articles
G	52.41 †	Retail sale of textiles
G	52.42	Retail sale of clothing
G	52.43 †	Retail sale of footwear and leather goods
G	52.44 †	Retail sale of furniture, lighting equipment and household articles n.e.c.
G	52.45 § †	Retail sale of electrical household appliances and radio and television goods
G	52.46 †	Retail sale of hardware, paints and glass
G	52.47	Retail sale of books, newspapers and stationery
G	52.48	Other retail sale in specialized stores
G	52.6 †	Retail sale not in stores
G	52.7	Repair of personal and household goods
H	55.1	Hotels
H	55.2 †	Camping sites and other provision of short-stay accommodation
H	55.3+55.4+55.5	Restaurants and Bars and Canteens and catering
I	60.1	Transport via railways
I	60.2	Other land transport
I	60.3 § †	Transport via pipelines
I	61.1 § †	Sea and coastal water transport
I	61.2	Inland water transport
I	62	Air transport
I	63.11	Cargo handling
I	63.12 †	Storage and warehousing
I	63.2	Other supporting transport activities
I	63.3	Activities of travel agencies and tour operators; tourist assistance activities n.e.c.
I	63.4 †	Activities of other transport agencies
I	64.1 †	Post and courier activities
I	64.2	Telecommunications
K	70.1 § †	Real estate activities with own property
K	70.2 †	Letting of own property
K	70.3	Real estate activities on a fee or contract basis
K	71.1 †	Renting of automobiles
K	71.2 †	Renting of other transport equipment

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Sector code	Industry code	Industry
K	71.3	Renting of other machinery and equipment
K	72.1	Hardware consultancy
K	72.2	Software consultancy and supply
K	72.3 § †	Data processing
K	72.4	Database activities
K	72.5+72.6 †	Maintenance and repair of office, accounting and computing machinery and Other computer related activities
K	73	Research and development
K	74.1	Legal, accounting, book-keeping and auditing activities; tax consultancy; market research and public opinion polling: business and management consultancy; holdings
K	74.20.0	Architectural and engineering activities and related technical consultancy
K	74.20.1	Architectural and engineering activities
K	74.20.2	Geological and prospecting activities
K	74.20.3	Geodetic surveying and cartographic activities
K	74.3	Technical testing and analysis
K	74.4 †	Advertising
K	74.5	Labour recruitment and provision of personnel
K	74.6	Investigation and security activities
K	74.7	Industrial cleaning
K	74.8	Miscellaneous business activities n.e.c.
O	90.00	Sewage and refuse disposal, sanitation and similar activities
O	90.01 § †	Collection and treatment of sewage
O	90.02 § ‡	Collection and treatment of other waste
O	90.03 †	Sanitation, remediation and similar activities
O	92.1	Motion picture and video activities
O	92.2	Radio and television activities
O	92.3+92.5	Other entertainment activities and Library, archives, museums and other cultural activities
O	92.4 †	News agency activities
O	92.6	Sporting activities
O	92.7	Other recreational activities
O	93.01	Washing and dry-cleaning of textile and fur products
O	93.02 § †	Hairdressing and other beauty treatment
O	93.03	Funeral and related activities
O	93.04 § †	Physical well-being activities
O	93.05 § †	Other service activities n.e.c

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