ISSN 2042-2695

CENTRE for ECONOMIC PERFORMANCE

CEP Discussion Paper No 1645

August 2019

The Best versus the Rest: Divergence across Firms during the Global Productivity Slowdown

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E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

Abstract

We document that labor productivity of the globally most productive firms – the “frontier” – has diverged from all other firms – the “rest” – throughout the 2000s. This divergence remains after controlling for capital intensity and markups, and is strongest in ICT services, indicative of “winner-takes-all” dynamics. We also find weakening catch-up and market selection below the frontier, which can explain why this divergence at the firm level is linked to weaker aggregate productivity. The divergence is found to be stronger in industries where product market regulations are less competition friendly, highlighting the need for regulatory policy to improve the contestability of markets.

Key words: firm dynamics, regulation, knowledge diffusion, technological change, productivity
JEL Codes: O30; O40; M13

This paper was produced as part of the Centre’s Growth Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

We are grateful to Daron Acemoglu, Ufuk Akcigit, Martin Baily, Eric Bartelsman, Giuseppe Berlingieri, Olivier Blanchard, Patrick Blanchenay, Nick Bloom, Erik Brynjolffson, Sara Calligaris, Gilbert Cette, Mirko Draca, Luis Garicano, John Fernald, Jonathan Haskel, Remy Lecat, Catherine L. Mann, Giuseppe Nicoletti, Dirk Pilat, Alessandro Saia, Louise Sheiner, Chad Syverson, John Van Reenen and Andrew Wyckoff, Jeromin Zettelmeyer for their valuable comments and suggestions.
We would also like to thank seminar participants at the Bank of England, Bank of Canada, the Brookings Institution, the Central Bank of the Netherlands, ESCoE, European Commission, France Strategie, IMF, MIT, NBER Productivity, Innovation and Entrepreneurship Program meeting, OFCE, Peterson Institute for International Economics, Royal Economic Society, UCL, US Census Bureau, and participants at the OECD Global Forum on Productivity Conferences in Mexico City and Lisbon as well as OECD Committee Meetings. The opinions expressed and arguments employed herein are solely those of the authors and do not necessarily reflect the official views of the OECD or its member countries.

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Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

Introduction

Aggregate productivity growth slowed in many OECD countries, even before the financial crisis, igniting a spirited debate on the future of productivity (e.g. Brynjolfsson and McAfee, 2011 *vs* Gordon, 2016).[2] This debate has been conducted, by and large, from a macroeconomic perspective, and implicitly concerns the prospects for innovation at the global productivity frontier. However, little is actually known about the productivity performance of this global frontier over time.[3] This is surprising since aggregate productivity and differences thereof across countries are increasingly being linked to the widespread heterogeneity in firm performance within countries and sectors (Syverson, 2011; Garicano, Lelarge, Van Reenen, 2016; Bartelsman, Haltiwanger and Scarpetta, 2013; Hsieh and Klenow, 2009).[4]

To better understand these phenomena, this paper utilizes cross-country longitudinal firm level data to shed new light on the evolution of this heterogeneity during the period of the slowdown. We focus on the global productivity frontier (the "best") – defined as the top 5% of firms in terms of labor or multi-factor productivity (MFP) levels within two-digit industries – and compare it with all other firms below the frontier (the "rest"). Our key finding is a rising productivity gap between the frontier – which shows robust growth – and all other firms below – which grow at a sluggish rate – during the 2000s. Put differently, we uncover that an important and so far overlooked feature of slow aggregate productivity growth in recent years is a rising divergence between the "best" and the "rest" in terms of firm-level productivity.[5]

We show that this rising labor productivity gap between global frontier and laggard firms largely reflects divergence in revenue based MFP (MFPR). We then explore the role of market

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[2] For further evidence on the nature and causes of the productivity slowdown, see, among others Fernald (2014), Cette, Fernald and Mojon (2016) and Syverson (2017).

[3] Throughout the paper we use the term "laggard" and "non-frontier" interchangeably – they refer to the group of firms that are not at the frontier.

[4] Recent theoretical work also established a link between macroeconomic productivity performance and the distance between leaders and laggards (Akcigit and Ates, 2019a, 2019b; Brynjolfsson, Rock and Syverson, 2018).

[5] In fact, we show in Section 3 that the two trends are systematically related: those industries that experience a large global divergence are also those where global productivity growth was weaker.

power and conclude that the divergence in MFPR is not primarily due to an increasing ability of frontier firms to charge higher markups. While we find evidence that market power of frontier firms has increased among services sectors, this amounts to less than one-third of the total divergence in MFPR. This leads us to the conclusion that the rising MFPR gap between global frontier and laggard firms is to a large extent a divergence in productivity or technology, broadly defined.[6]

In addition to documenting this divergence at the global level, a key contribution of the paper is shedding light on the potential drivers of this trend from three different angles. First, we investigate the presence of winner-takes-all dynamics (Brynjolfsson and McAfee, 2011), then we test whether there is evidence for a slower catch-up of productivity to the frontier. Finally, we highlight several aspects of declining business dynamism more generally.

In particular, we find three distinct patterns that are supportive of the winner-takes-all hypothesis. First, there is an increase in the market share by the frontier, which is more pronounced in ICT services – a sector that is generally characterized by very low marginal costs. Second, divergence in MFP itself is stronger within ICT services – in particular within data services. Third, within the global frontier, the productivity of the "most elite" segment of firms (captured by the top 2%) has risen relative to that of other segments of the frontier already high up in the productivity distribution (top 5% or top 10%). This pattern again is strongest in ICT and data services, where the gap between the top and the rest of the distribution has increased very strongly (up to 0.6-0.9 log-points) compared to other services (by 0.3 log-points).

Next we test whether the rate of productivity catch-up has declined, which would be indicative of weaker knowledge diffusion from the frontier to laggard firms. We estimate the rate of convergence to the global productivity frontier for sub-periods of our sample and find a marked decline over time. Consistent with this, we also find that persistence at the frontier has increased. These patterns suggest a more difficult entry to the top segment of the distribution and a slowdown in the catch-up of firms below the frontier.[7]

[6] Such broader definition encompasses not only technological innovation but also the capacity of tacitly combining various intangibles – computerized information, innovative property and economic competencies (Corrado, Hulten and Sichel, 2009) as well as management (Bloom and Van Reenen, 2007) – in business processes.

[7] See complementary and supporting evidence in Bahar (2018) who documents that the strength of convergence is weaker close to the top of the distribution. These findings about weaker convergence exclude explanations for the

The third aspect among the potential drivers of the diverging trend is business dynamism. We document a slowdown in the growth enhancing nature of market selection, captured by two key patterns. First, we find a decline in the share of young firms coupled with a higher productivity threshold for entrants. In parallel, we also document a higher survival probability of firms with persistently weak profitability which would typically exit in a competitive market.

We then also test the aggregate implications of this divergence. A rising productivity gap in itself can be related to either faster or slower aggregate productivity growth, depending on the relative strength of the contribution of the fast growing frontier or the sluggish performance of all other firms below. To establish that the rising productivity gap is indeed a key feature of the productivity slowdown throughout the 2000s, we test the relationship between industry aggregate productivity growth and the degree of firm-level divergence between the best and the rest. We find negative and statistically significant relationships across several alternative productivity and frontier measures, indicating that the two phenomena are linked.

Finally, we investigate the role of the regulatory environment in driving the increasing productivity gap between the frontier and lagging firms. Declining business dynamism suggests that the stagnation in the productivity growth of laggard firms may be connected to rising barriers to entry and a decline in the contestability of markets (Furman and Orszag, 2016). Regulations that are not reformed to adjust to structural changes could lead to weakening competition among firms and could thus lower their incentives to adopt the latest technologies and business practices. In line with this hypothesis, we show – using a difference- in-difference estimation with instrumental variables – that MFP divergence is more pronounced in sectors where pro-competitive product market reforms or deregulation were least extensive.

Our paper builds on previously established facts about the large and persistent heterogeneities that are present across firms in terms of productivity levels, even in narrowly defined sectors (Bartelsman and Doms, 2001; Syverson, 2004 and 2011). It also links to several strands of a more recent literature that document structural changes in the economy. Many of them developed since our research on the global frontier started,[8] but they typically focus on the US or

divergence based on a large or rising variance of firm-level productivity growth – if anything, they are consistent with more persistence.

[8] See Andrews, Criscuolo and Gal (2015).

selected European countries individually. In particular, several studies have shown an increasing dispersion in firm-level outcomes that are closely related to productivity, such as firm size (see the work on "Superstar firms" and rising concentration by Autor et al, 2017a, 2017b; Covarrubias, Gutiérrez and Philippon, 2019), wages (Song et al, 2018), profits and financial returns (Furman and Orszag, 2016) and markups (De Loecker, Eeckhout and Unger, 2018; Calligaris, Criscuolo and Marcolin, 2018).[9] Many of these papers find a link between these structural changes and increasing digitalization and globalization, which could induce a change in the production technology with "winner-takes-all" features or an increased role for intangible capital in production (Crouzet and Eberly, 2018). Our findings also relate to the literature on the rising misallocation across firms (Gopinath et al, 2017) and how changes in dispersion across firms are related to aggregate productivity developments (Foster et al, 2018).

The divergence of productivity across firms is also consistent with recent evidence on how technologies spread across countries and firms. Adoption lags for new technologies across countries are falling, but in parallel, penetration rates within countries are lower than before (Comin and Mestieri, 2018). Put differently, new technologies developed at the global frontier are spreading more and more rapidly across countries but their diffusion to all firms within any economy is slowing, with many available technologies remaining unexploited by a non-trivial share of firms. This is consistent with the evidence of Autor et al (2017b) who show that slower citation speeds are associated with stronger concentration in sectors.

Indeed many recent theoretical explanations for the rise in the heterogeneity of firm-level performance include a slowdown or a delay in the diffusion of recent general purpose technologies (Akcigit and Ates, 2019a, 2019b; Brynjolfsson, Rock and Syverson, 2018; Benhabib, Perla and Tonetti, 2017).[10] Other theories link it to very low interest rates, which can lead to stronger incentives for industry leaders to invest and preserve their strategic advantage than lagging firms – if the gap between the two is sufficiently large (Liu, Mian and Sufi, 2019). Yet another theory

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[9] A series of papers have also documented an increase in productivity dispersion within individual countries: for the US, see Decker et al (2016), Bahar (2018), Bessen (2017), and Brown, Dinlersoz and Earle (2016); for the UK, see Faggio, Salvanes and Van Reenen (2010); for France, see Cette, Corde and Lecat (2018); and for several individual OECD countries, see Berlingieri, Blanchenay and Criscuolo (2017).

[10] For an earlier literature on the diffusion of technologies across firms, see Jovanovic and MacDonald (1994). For the role of imitation by the least productive firms in their productivity catch-up, see Perla and Tonetti (2014).

focusing on productivity divergence in the post-crisis period, points to cyclicality in technology adoption efforts by firms as a potential driver (Anzoategui et al, *forthcoming*).

The next section discusses the firm level data and productivity measurement issues, before identifying and describing the characteristics of firms at the global productivity frontier. Section 2 presents new evidence on labor productivity divergence between global frontier and laggard firms, while also explores the robustness to this result to controlling for capital deepening and markups. Section 3 explores potential structural drivers such as winner-takes-all dynamics and slowing convergence, highlighting the aggregate implications. Section 4 establishes a significant impact of product market regulation on the size of the MFP gap. The final section concludes.

1. Data and Measurement

This paper relies on a longitudinal cross-country firm-level database (Orbis) using harmonized company accounts and covering 24 OECD countries[11] over the period 1997 to 2014 for the non-farm, non-financial business sector.[12] These data are sourced from annual balance sheet and income statements, collected by Bureau van Dijk (BVD) – an electronic publishing firm – using a variety of underlying sources ranging from credit rating agencies (Cerved in Italy) to national banks (National Bank of Belgium for Belgium) as well as financial information providers (Thomson Reuters for the US).[13]

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[11] These countries are all from the OECD: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Great Britain, Greece, Hungary, Ireland, Italy, Japan, Korea, Latvia, Luxembourg, Netherlands, , Poland, Portugal, Spain, Sweden, Slovenia and the United States. The country coverage is somewhat smaller in the policy analysis. The Orbis database tends to have a better coverage for European countries, while the US segment is basically the listed companies (Gal, 2013; Kalemli-Ozcan, Karabarbounis and Villegas-Sanchez, 2015; Bureau van Dijk, 2016). This means that the global *frontier* firms are likely to be captured, even though coverage for European ones are more complete. To mitigate any concerns arising from the coverage of *laggard* firms, the regressions throughout the paper include a rich set of fixed effects, which control for country- and year specific differences.

[12] This means retaining industries with 2 digit codes from 5 to 82, excluding 64-66 (financial services) in the European classification system NACE Rev 2, which is equivalent to the international classification system ISIC Rev. 4 at the two-digit level. In most of our discussion below we focus on two sector-groups: manufacturing (spanning 2-digit sectors 10 to 33) and business services, or services in short form (sectors 45 to 82, excluding financial services).

[13] See the full list of information providers to Bureau van Dijk regarding financial information for the set of countries retained in the analysis in Appendix F.

Orbis is typically recognized as the largest available cross-country company-level database for economic and financial research and it (or its European segment Amadeus) serves as the standard source for cross-country firm level studies (Gopinath et al, 2017). However, since the information is primarily collected for use in the private sector typically with the aim of financial benchmarking, a number of steps need to be undertaken before the data can be used for economic analysis. The steps we apply closely follow suggestions by Kalemli-Ozcan et al (2015) and previous OECD experience (Gal, 2013; Ribeiro, Menghinello and de Backer, 2010).[14] Three broad steps are: *i*) ensuring comparability of monetary variables across countries and over time (industry-level PPP conversion and deflation); *ii*) deriving new variables that will be used in the analysis (capital stock, productivity); and *iii*) keeping company accounts with valid and relevant information for our present purposes (filtering or cleaning). Orbis is a subsample of the universe of companies for most countries, retaining the larger and hence likely more productive firms. To mitigate problems arising from this – particularly the under-representation of small firms – we restrict our sample to firms with more than 20 employees on average over their observed lifespan. For more details, see Appendix F.

1.1 Productivity measurement

As a starting point, we focus on labor productivity, which is calculated by dividing real value added (using country specific two-digit industry deflators, combined with 2005 industry-level USD PPPs) by the number of employees. Labor productivity – besides its simplicity – also has the advantage that it retains the largest set of observations, as it does not require the availability of measures for fixed assets or intermediate inputs (proxied by materials m_t) potentially used for deriving multi-factor productivity (MFP).

Our baseline MFP is derived from a value added based production function estimation using the widely used Wooldridge (2009) control function based methodology, with the number of employees and real capital stock as inputs and materials as the proxy variable. More specifically,

[14] We are grateful for Sebnem Kalemli-Ozcan and Sevcan Yesiltas for helpful discussions about their experience and suggestions with the Orbis database.

we assume a value added based Cobb-Douglas production function and estimate regressions of the following form (equation (1)), separately for each two-digit industry j:

$$y_{it} = \beta_K^j k_{it} + \beta_L^j l_{it} + \nu_c^j + \eta_t^j + \varepsilon_{\mathrm{it}}, \text{ for all industries } j=1,\ldots J \quad (1)$$

where y_{it} denotes log of real value added, k_{it} denotes the log of real capital stock, and l_{it} the log of the number of employees. ν_c^j and η_t^j are country and year fixed effects, respectively (allowed to vary for each 2-digit industry), and $\varepsilon_{\mathrm{it}}$ is the error term. In order to mitigate the limitations from not observing firm-level prices, we also correct our revenue based MFP measure (MFPR) by firm- and time-varying markups applying the markup estimation methodology of De Loecker and Warzynski (2012) and defining markup corrected MFPR as the difference between MFPR and markups (both measured in logs; see details in Appendix F.)

1.2 Measuring the productivity frontier

In keeping with the existing literature (e.g. Bartelsman, Haskel and Martin, 2008), we define the global productivity frontier in a very clean and transparent manner: it is the top 5% of firms in terms of (log) productivity levels, within each detailed industry and year.[15] Using an MFPR-based productivity frontier definition, for example, results in a global frontier size of about 80 companies for the typical industry (more specifically, the median is 83 for "manufacturing of basic metals"). For the sectors populated with a large number of businesses, the frontier represents about 400-500 companies (e.g. in retail or wholesale trade or construction).

Importantly, and in line with the existing literature, the *set* of frontier firms is allowed to change over time. This choice is necessary to ensure that when assessing the evolution of the global frontier, we account for turbulence or churning at the top: some firms can become highly

[15] As the coverage of firms may change over time, we keep the frontier number fixed over time in our baseline definition. Specifically, we use the top 5% of the median number of firms (across years), separately by each two-digit industry. This still allows for inherent differences in the size of industries in terms of the number of firms. As Figure A5 in Appendix A shows, the choice among alternatives (fixed absolute number or a different threshold, at 10%) does not affect the main finding of a growing productivity gap between the frontier and the rest. The diverging pattern is also robust to using a time-varying 5% for defining the number of frontier firms, see Andrews, Criscuolo and Gal (2015), Figure A1 and regression results in this paper (Table A1, Panel A, in Appendix A).

productive and enter the frontier, while other, previously productive businesses can lose their edge and fall below the frontier. This is symmetric to the treatment of the group of firms below the frontier, whose composition is also allowed to change through entry and exit. As will be discussed in Section 3, there is indeed substantial churning at the frontier, mostly concentrated amongst the top quintile of the productivity distribution. But our finding of productivity divergence is robust to using moving average firm-level productivity, which is a more persistent measure of firm performance (Appendix A).

1.3 Characteristics of firms at the frontier

Table 1 reports the cross-sectional differences in the average characteristics for firms at the global frontier relative to other firms in 2013, along a number of dimensions. Panel A reports these differences based on a labor productivity measure while Panel B does likewise using MFP. A number of key findings emerge.

First, firms at the global productivity frontier are on average 3 to 4 times more productive than non-frontier firms.[16] At first glance, these differences appear large but are to be expected given the already widespread heterogeneity in firm productivity that is typically observed within narrowly defined sectors within single countries (Syverson, 2004).[17,18] Second, on average, global frontier firms have larger sales and are more capital intensive, and more so for labor productivity. In manufacturing, firms at the frontier in terms of MFP (both MFPR and its markup corrected

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[16] Note that productivity is measured in logs, so the difference in Panel A for manufacturing firms between frontier and laggard firms of 1.3 translates into a ratio of $\exp^{1.3}$=3.6 times more productive frontier than laggards firms.

[17] For example, within 4 digit manufacturing industries in the United States, Syverson (2004) finds a 2-to-1 ratio in value added per worker between the 75th- and 25th-percentile plants in an industry's productivity distribution. Including more of the tails of the distribution amplifies the dispersion, with the average 90–10 and 95–5 percentile labor productivity ratios within industries in excess of 4-to-1 and 7-to-1, respectively. Note also the most studies focus on productivity dispersion in a single country, while our analysis pools together different countries, potentially further widening the productivity distribution.

[18] A large literature motivates how such large differences in productivity can be sustained in equilibrium, despite market selection and the reallocation of resources being an equalizing force over the longer run. Supply-side explanations have typically emphasized factors related to technology shocks, management skill, R&D, or investment patterns (Bartelsman and Doms, 2000). The demand side also appear relevant, given evidence that imperfect product substitutability – due to geographical segmentation (i.e. transport costs), product differentiation (i.e. consumer preferences, branding/advertising) and intangible factors (customer-producer relationships) – can prevent industry customers from easily shifting purchases between industry producers (Syverson, 2004).

variant) have significantly higher employment than laggards, in line with existing evidence that productivity is positively correlated with size (Berlingieri, Calligaris and Criscuolo, 2018). However, frontier firms do not employ a significantly larger number of employees in services for any of the productivity measures analyzed, in line with recent evidence that gathers several country-level firm-level datasets (Berlingieri, Criscuolo and Calligaris, 2018). Third, global frontier firms pay also higher wages. Finally, they are also more likely to belong to a multinational group/conglomerate and patent more intensively than other firms.[19,20]

2. Productivity Divergence between the Frontier and the Rest

This section documents the evolution of productivity for the frontier and non-frontier firms, revealing a robust and ubiquitous divergence between the two groups. Figure 1 describes the evolution of labor productivity for firms at the global productivity frontier and for all other firms below the frontier. It shows how the unweighted average of log labor productivity across firms in these two groupings evolved over time, with the initial year – 2001 – indexed to 0 and separately for two broad sectors: manufacturing and non-financial market services (or services, in short form).[21]

Between 2001 and 2013, firms at the global frontier have become relatively more productive, with their labor productivity increasing at an average annual rate of 2.8 log points in the manufacturing sector, compared with productivity gains of just 0.6 log points per annum for laggards. This divergence is even more pronounced in the services sector, with labor productivity

[19] This is based on analysis for 2005 using a different vintage of the Orbis firm-level database used in our previous work (Andrews, Criscuolo and Gal, 2015).

[20] Numerous well-known multinational companies are part of the frontier, such as Google, Apple, Amazon or Microsoft among ICT services, Samsung, Nokia, Siemens among electronics manufacturing as well as BMW, Ford and Volkswagen within car manufacturing.

[21] Our aim with the graphical representation is merely to show the evolution of frontier productivity compared to other firms in a way that captures the average tendencies across all economic activities or technologies. When weighting by the number of firms, employees or value added *across* industries, the qualitative picture of divergence remains. Note also that we restrict the time horizon of the figures between 2001 and 2013 because the years before the 2000s and the latest year (2014) are less well covered in Orbis. In regressions where we can control for a rich set of fixed effects capturing potential changes in coverage, we can utilize a longer span of data (1997-2014).

at the frontier growing, on average, by 3.6 log points, compared to an average of just 0.4 log points for the group of laggards. The divergence is statistically significant and significantly stronger among services, as the next section will document.

Since gains in labor productivity can be achieved through either higher capital intensity or multi-factor productivity (MFP), Figure 1 panel B plots the evolution of these two components for global frontier and non-frontier firms. The global frontier in now redefined in terms of the top 5% of firms in MFPR levels within each two digit industry and year, thus abstracting away from productivity trends driven by changes in capital intensity.[22] Divergence between the top and the rest of the distribution is still present, to a similar degree as with labor productivity. Since our capital measure is based on balance sheet information, it incorporates both tangible and intangible assets, although only a limited set of the latter, such as software, data and R&D (Bureau van Dijk, 2016). It misses some other elements such as the value of patents, brand-building, worker training and the development of organizational practices (Corrado, Hulten and Sichel, 2009). To the extent that the most productive businesses implement more and more of these type of investments, and at a faster pace than other firms, this may contribute to a widening gap in our measured MFP.[23] Accordingly, our interpretation on the likely drivers of MFP divergence takes into account that measured MFP reflects these and other factors beyond narrowly defined technology or technical efficiency – such as management practices or tacit knowledge, more generally (e.g. Syverson, 2011).

Given that our measure of multifactor productivity (MFPR) is based on information on revenues and that firm-level prices are not available, its divergence might also reflect the increasing market power of the frontier. This in turn would require a shift of our focus toward profitability as opposed to productivity (including technical efficiency and business practices). Accordingly, we attempt to assess the contribution of markup behavior to MFPR divergence, using

[22] Using labor productivity to define the frontier group of the top 5%, the divergence of MFPR is very similar (Figure A2 in Appendix A). The diverging MFPR patterns are robust to using alternative definitions of MFPR, based on a constant returns to scale elasiticity for labor (based on industry aggregate labor shares) and capital (Solow residual) or the Wooldridge (2009) gross-output based production function estimation approach (Figure A7 in Appendix A) and to using materials (a proxy for intermediate inputs) as the fully flexible input in De Loecker and Warzynski (2012) markup correction methodology for a subset of 18 countries for which data are available (Figure A6 in Appendix A).

[23] As a flipside to this issue, our value added measure subtracts spending on these intangibles as costs. As discussed in Corrado, Hulten and Sichel (2009), overall, the underestimation of capital and value added tends to lead to an upward bias on MFP.

the methodology outlined in Appendix F. Once we correct MFPR for markups and redefine the frontier using such corrected MFPR, the diverging pattern and its magnitude remains similar to the one with MFPR (Figure 1, Panel C).[24]

Given potential concerns of coverage variations in Orbis, Figure A1 in Appendix A also reports figures for the industry aggregates sourced from the OECD National Accounts. Comparing the frontier with industry aggregates tends to understate the true gap between frontier and laggard firms as frontier firms will also inflate industry level productivity, particularly when their weight is large and/or growing. This is because the evolution of industry aggregate productivity over time reflects not only within-firm productivity developments but also changes in allocative efficiency.[25] Reassuringly, industry level trends look very much in line with the picture obtained with information from Orbis, with the aggregate lines falling between the frontier and the laggard group, tracing more closely the variation observed for laggards.

As illustrated in Appendix A, the divergence is also robust to: *i)* using revenue-based (instead of value added based) labor productivity (Figure A4), *ii*) defining the global frontier in terms of the top 100 firms or the top 10% of firms instead of the top 5% (Figure A4); *iii)* taking median labor productivity in the frontier and non-frontier firms groupings as opposed to average productivity; *iv)* excluding from the sample firms that are part of a group (i.e. subsidiaries), either domestic or multinational, where profit-shifting activity may be relevant (Figure A6); *v)* using labor costs as labor inputs hence controlling, at least partly, for changes in skills and hours worked to the extent that they are reflected in wages (Figure A7, Panel C); *vi)* defining the frontier based on the average of productivity levels across three consecutive years instead of based on single years (Table A1)*; vii)* and using more narrowly-defined industries (i.e. 3 and 4-digit industry classifications instead of two-digit ones) to better ensure that the firms compared against each

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[24] Using a frontier definition based on non-corrected MFPR shows that (Figure A3 in Appendix A) rising markups for frontier firms plays only a moderate role and only for services: it captures roughly 1/3rd of the total divergence in the pre-crisis period – but this divergence in markup behavior is mostly unwound in the post-crisis period.

[25] Further, the aggregate labor productivity measures from the industry data also reflect developments among the smallest companies (below 20 employees) as well as the self-employed. As such, it is not strictly comparable with the frontier and non-frontier firms but still provides a benchmark against which the patterns obtained using the Orbis sample can be compared.

other are competing in the same market and producing similar products (Figure A9-Figure A11).[26,27]

3. Potential Drivers and Aggregate Implications

The evidence presented so far suggests that the MFP gap between the global frontier and other firms has risen significantly over time and that this pattern has emerged even before the crisis. We provide additional evidence that suggests that the top of the distribution, the frontier, may be affected by *winner-takes-all* dynamics. At the same time, stalling diffusion of knowledge and best practices, coupled with diminished market dynamism could inhibit productivity in the distribution of firms below the frontier. In practice, it is difficult to distinguish the exact relative importance and the causal nature of these factors. The findings presented below suggest that a combination of them is likely to be at play. This is further corroborated by simple numerical simulations in Appendix B, which illustrate that the strength of the catch-up process has to weaken over time, market selection has to be relatively weak and likely worsening so as to produce a diverging pattern between the frontier away and all other firms.

3.1. "Winner-takes-all" dynamics likely to boost the frontier

The productivity divergence patterns unveiled so far may partly reflect the increasing potential for digital technologies to unleash winner-takes-all dynamics (Brynjolfsson and McAfee, 2011). Our findings below support the existence of such tendencies. First, divergence in MFPR is

[26] In some instances, however, this leads to a non-trivial reduction in the number of firms within each sector – raising difficulties for production function estimation and increasing the prevalence of idiosyncratic and noisy patterns. This leads us to conduct our baseline analysis at the two-digit level.

[27] In order to avoid estimating production functions with too few firms per industry, the production function parameters are still estimated at the two-digit level and only the frontier definition is applied at the 3 or 4 digit level. The median number of firms across two-digit sectors and years is about 2000, but this figure falls to 210 and 130 for 3 and 4 digit sectors respectively. When looking across country*industry*year cells, these medians are 53, 8 and 6, respectively for 2, 3 and 4 digit industries. Thus, we chose the two-digit detail level as our benchmark, which is a compromise between avoiding too small cells and the appropriate differentiation across economic activities.

accompanied by divergence in revenues – or market shares – between frontier and laggard firms, Figure 2 (Panel A) shows that the gap in revenues has been growing over time: global frontier firms have gained significant market share relative to laggards in manufacturing and to a larger extent in services. In contrast, the average size of frontier firms and laggards in terms of employment show similar trends (Panel B).

Second, these patterns appear to be particularly strong in sectors providing ICT services where cost advantages coming from the virtually zero-cost replication of information goods and business processes are reinforced with network externalities that favor the emergence of a few dominant players (e.g. providing a specific network, platform or standard). Figure 3, Panel A shows that divergence in revenues is particularly stark in ICT services compared to services outside the ICT segment. This divergence is also apparent within the global frontier grouping: the sales of firms in the top 2% of the global MFPR distribution grew by 14% on average in ICT services over the sample period, compared to 7% in other services.[28] In comparison, the sales of the top 5% have grown by 6% and 3.5% in ICT and other services, respectively.

Third, our results show a more pronounced MFP divergence in ICT services between frontier and laggard firms as well as within the global frontier grouping. Figure 3 (Panel B) shows that the rise in the MFPR gap is very pronounced in ICT services and especially so in data services (Panel C).[29] Moreover, within the global frontier grouping, a small cadre of the most elite firms (top 2%) have become more productive relative to other frontier firms in ICT and data services, while this pattern is not evident for other services sectors.

Table 2 illustrates the key findings on productivity divergence by means of firm-level regression results with appropriate fixed effect structures. The starting point for the specification is the following:

$$MFP_{jit} = \alpha T_t + \beta F_{jit} T_t + \eta_j^F + \varepsilon_{jit}, \qquad (2)$$

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[28] Given the relative volatility of the sales data for firms in the top 2% of global MFPR distribution, we do not show these estimates for presentational reasons.

[29] This is also in line with findings by Gamberoni, Giordano and Lopez-Garcia (2016) using alternative firm-level sources, which show strongest increases in capital-productivity dispersion in the ICT sector. Decker et al (2016) also confirm this for labor productivity for the US.

where MFP_{jit} stands for firm-level productivity in industry *j* for firm *i* in year *t*, T_t is a linear time trend and F_{jit} is binary variable capturing frontier status (1 - at the frontier; 0 - below the frontier). η_j^F stands for a full set of fixed effects capturing each sector and frontier status (effectively, interacting F_{jit} with sector fixed effects η_j) to control for the average difference between frontier and non-frontier firms separately for each sector, and ε_{jit} is the error term. Based on the diverging patterns in Figure 1, a positive and significant β coefficient is expected, implying that the productivity frontier shows a steeper positive trend than firms below the frontier.

The specification in equation (2) is enriched so that we can directly test for differences in the degree of this divergence *i)* between services versus manufacturing (as shown in the right vs left panels of Figure 1 on the one hand, and *ii)* between ICT services and other services (as shown in Figure 3) on the other hand:[30]

$$MFP_{jit} = \alpha T_t + \beta F_{jit} T_t + D_{Ser}\left(\alpha_{Ser} T_t + \beta_{Ser} F_{jit} T_t\right) + D_{IT}\left(\alpha_{IT} T_t + \beta_{IT} F_{jit} T_t\right) + \eta_j^F + \varepsilon_{jit} \qquad (3)$$

where the subscripts Ser and IT stands for services and IT related services, respectively, and $D_{Ser} = 1$ if the sector belongs to services and 0 otherwise, and $D_{IT} = 1$ if the sector is IT services and 0 otherwise. In this formulation, $\beta_{Ser} > 0$ indicates faster divergence in services between frontier and other firms than in manufacturing, and $\beta_{IT} > 0$ indicates that this divergence is even faster among data services (since $D_{Ser} = 1$ for all services sectors, including IT services).

Table 2 confirms the statistical and economic significance of the diverging pattern, showing less than 0.1% per year average growth for firms below the frontier and 2% per year growth of the frontier in manufacturing. This diverging trend is 1% per year faster in services and an additional 3% per year faster in data services. These figures are broadly similar for labor productivity (column 1) and variants of MFP (columns 2 and 3). The results are also qualitatively robust to different variations of defining the frontier: (i) using three-year moving averages of firm-

[30] Within ICT services, we focus on "Data services" which is sector 63 in ISIC Rev. 4 ("Information service activities", comprising of "Data processing, hosting and related activities; web portals") and it captures the type of activity that is most like to be characterized by zero marginal costs and winner-takes-all dynamics. Google, for instance, is classified in this sector.

productivity, to avoid the possibility that the frontier is growing simply due to the large and potentially increasing variance of year-to-year productivity changes (for instance, due to more and more concentration of output in certain years) and (ii) allowing the set of firms in the frontier group to vary over time with the sample (a time-varying 5%) (See Table A1 in Appendix A).

We also test for further divergence at the very top of the productivity distribution and compare how this varies across sectors to see whether the patterns seen in Figure 3 are statistically significant. The following specification is estimated, where notations are the same as for equations (2) and (3):

$$MFP_{jit} = \alpha T_t + \beta F_{jit}^{10} T_t + \gamma F_{jit}^{5} T_t + \delta F_{jit}^{2} T_t + \eta_j^F + F_{jit}^{10} + F_{jit}^{5} + \varepsilon_{jit} \tag{4}$$

with F_{jit}^{10} denoting the indicator for the firm being in the top 10% of the productivity distribution in year *t* (within the firm's industry), F_{jit}^{5} and F_{jit}^{2} similarly for being in the top 5% and top 2%, respectively. This regression is estimated separately for manufacturing, services and IT services, and we expect to find positive and significant estimates for β for all three cases, with positive and significant γ or δ for IT services. Indeed, there is strong and significant divergence at the top end of the distribution for IT services: the most productive 2% has a stronger divergence away from the segment just below, i.e. the top 5% excluding the top 2%, by 3.4% per annum for labor productivity and by 2.2% per annum for MFP (Table 3 columns 5 and 6).

3.2. Slower catch-up and weakening market dynamism holding back firms below the frontier

The rising gap in MFP between frontier and laggard firms could also signal stalling diffusion of technology and business practices, as well as sluggish market dynamism amongst laggards. To test whether the pace of productivity convergence has slowed over time, we estimate a model where firm level MFP growth depends on a firm's lagged MFP gap with (or distance from) the global frontier. The empirical specification is based on the estimation of the Acemoglu, Aghion and Zilibotti (2006) framework, which has been implemented in a number of studies (e.g. Griffith, Redding and Simpson, 2009). In particular, the log of MFP is assumed to follow an error correction model of the following form:

$$\Delta MFP_{jit} = \sum_{k} \delta_k \, GAP_{ji,t-1} D_t^k + \gamma \Delta MFP_{jt}^{Frontier} + \sum_{m} \phi_m \, X_{it}^m + \eta_{ct} + \eta_j + \varepsilon_{jit} \qquad (5)$$

Productivity growth ΔMFP_{jit} of firm i is expected to increase with the size of the productivity gap (hence $\delta_k > 0$), which measures how far each firm is away from the frontier $MFP_{jt}^{Frontier}$ in industry *j* in which firm *i* operates:

$$GAP_{jit} = MFP_{jt}^{Frontier} - MFP_{jit}.$$

We allow for the speed of productivity convergence to vary over time by including interaction terms of the speed of convergence $GAP_{ji,t-1} D_t^k$, where D_t^k is a dummy variable corresponding to different time periods (i.e. 1997-2000, 2000-2002 … 2010-2014). If the pace of MFP convergence slowed over time, then we expect the $GAP_{ji,t-1} D_t$ terms that belong to later periods to be significantly smaller than for earlier periods. The specification also includes a number of controls among X^m – such as detailed firm size and firm age classes, included separately in the baseline and interacted with the frontier growth and gap terms as an extension – as well as both industry η_j and country*time fixed effects η_{ct}. The standard errors are clustered by country and sector to allow for correlation of the error term in an unrestricted way across firms and time within sectors in the same country (Moulton, 1990).

The main conclusions from these regressions are shown visually in Figure 4, while detailed results are presented in tables in Appendix C. They demonstrate that the pace of productivity convergence has indeed declined significantly over time. In particular, the estimated coefficient on the lagged MFP gap term $GAP_{ji,t-1}$ declined by almost 30% from the late 1990s to the most recent period, with most of the fall realized by 2007, that is, before the start of the crisis (Appendix C, Table C1). The decline in the speed of catch-up is even more pronounced when the model is estimated using markup corrected MFPR (Figure 4 Panel B). This pattern holds when controlling for the different speed of catch-up by firm size and age or when using a richer set of fixed effects (interacted industry - year) that absorb the frontier terms in equation (5) hence do not depend on the exact measurement of the frontier (Appendix C, Table C2 and Table C3, respectively).

One symptom of stalling diffusion could be the increasing persistence of incumbents at the frontier, or that entry to the frontier increasingly comes from firms already close to it (i.e. within the top decile or top quintile of the distribution). We might also expect these patterns to be especially evident in the services sector where intangibles and tacit knowledge are becoming ever more important and where the increase in market power at the frontier is most apparent.

Indeed, in the beginning of the 2000s (2001-2003), half of MFPR-frontier firms in the services sector were made up from firms previously at the frontier or close to it (See Appendix C, Table C4, Panel A). More specifically, 48.3% of them were classified as frontier firms one year earlier according to our definition (top 5%), while 62% (68.8%) of them came from the top decile (quintile). By 2011-2013, however, these figures had risen to 55.2%, 71.1% and 77.4%, respectively. These patterns – which are also evident for mark-up corrected MFP, and to a lesser extent among manufacturing firms – suggest that it has become more difficult for laggard firms outside the top quintile of the MFP distribution to enter the top 5% frontier group.

Rising entrenchment at the frontier is consistent with the broader decline in business dynamism (entry and exit rates) observed across OECD countries (Decker et al, 2014 for the US and Criscuolo, Gal and Menon, 2014 for 18 countries). To explore the role of market dynamism more directly among laggard firms, Figure 5 distinguishes between four groups of firms: *i*) young firms (aged 0-5 years) to proxy for recent entrants; *ii*) mature firms (aged 6 to 10 years); *iii*) firms that should be close to exit in a competitive market, proxied by non-viable firms older than 10 years (those that record negative profits over at least two consecutive years); and *iv*) all other firms (i.e. viable old firms; the excluded category). Two key patterns emerge. First, firm turnover has fallen, as reflected by a decline in the share of young firms and a higher survival probability of marginal firms that would typically exit in a competitive market (Panel A).[31] Second, the average productivity of recent entrants relative to viable incumbent firms has risen, while the average productivity of firms on the margin of exit has fallen over time (Panel B). Indeed, the decline in firm turnover coupled with an increase in the implied productivity gap between entering and

[31] We use these categories to have a more robust picture of market dynamism and selection instead of working directly with entry and exit rates. They tend to be more volatile and noisy, in particular because our sample contains only those firms which have at least 20 employees on average over their observed lifespan. Also, the incidence of non-viable firms is likely to be understated since we compute them for the sample where MFP is available, and this excludes cases with negative value added, i.e. firms that have larger negative profits (in absolute value) than labor costs. For a more detailed analysis on the rise of non-viable firms, see Adalet McGowan et al (2018).

exiting businesses is what one would typically observe if barriers to entry had risen (Bartelsman, Haltiwanger and Scarpetta, 2009).

3.3. Divergence across firms and aggregate productivity growth

Aggregate productivity growth was slowing during the period for which we document productivity divergence. However, divergence in itself can be related to either faster or slower aggregate productivity growth. Indeed, if the frontier is growing faster, its contribution to aggregate productivity can increase, especially if the frontier also becomes relatively larger over time.[32] On the other hand, a weakening performance of firms below the frontier may result in lower aggregate productivity, either through slower catch-up or through weaker market selection, as the previous section illustrated.

Which of the two forces dominates is an empirical question. To test whether divergence and weak aggregate productivity growth performance are systematically linked, we exploit the cross-sectional (industry-level) variation in divergence and productivity growth[33]. We run the following baseline regression at the global industry-year level with aggregate industry productivity ($MFP_{jt}^{Aggregate}$) growth as the dependent variable and the speed of divergence (the change in the productivity gap from the frontier, $GAP_{jt} = MFP_{jt}^{Frontier} - \overline{MFP}_{jt}^{BelowFrontier}$) as the explanatory variable:

$$\Delta^{ld} MFP_{jt}^{Aggregate} = \beta \Delta^{ld} GAP_{jt} + \eta_j + \eta_t + \varepsilon_{jt}, \qquad (6)$$

where Δ^{ld} denotes the long-difference operator (over 5-years in the baseline), η_j and η_t denote industry and year fixed effects, $\overline{MFP}_{jt}^{BelowFrontier}$ represents the average MFP of firms below the frontier in industry *j* and year *t,* and all productivity measures are expressed in logs. A negative estimate for β would indicate that in industries where divergence is stronger, productivity growth

[32] Figure 2 suggests that the frontier group does not become larger in terms of employment: the pace of employment growth is roughly similar both at the frontier and below it.

[33] Relying only on the time series at the aggregate level would restrict us to very few data points.

is weaker, conditional on time-varying global factors (captured by η_t) and industry-specific trends (captured by η_j , considering that the variables in the regressions are growth rates).

We run this regression in several variants, defining the frontier and below frontier values based on the mean of log-productivity across firms (columns 1 and 3) or the median (columns 2 and 4), and using either MFP or labor productivity growth as dependent variable (columns 3 and 4). We define global industry aggregate MFP by weighting firm-level log MFP by a composite input index $\exp(\hat{\beta}_K^j k_{it} + \hat{\beta}_L^j l_{it})$, using the industry specific coefficient estimates for capital and labor elasticities from equation (1). Analogously, we define aggregate labor productivity by weighting up firm-level labor productivity using employment weights.

As Table 4 shows, there is a significant negative relationship between the increase in the productivity gap and aggregate productivity growth. This result is robust to i) changing the length of the period over which the gap changes and aggregate growth rates are defined (from 5 years to either 4 or 6 years), ii) to using an alternative definition of the frontier, iii) generally, also to defining the gap based on labor productivity instead of MFP (Table D1-Table D3 in Appendix D). Finally, the result is also robust to including the relative size of the frontier, with only a slightly weaker negative relationship and an insignificant term for the relative size variable, suggesting that changing allocative efficiency between the frontier and other firms is not an important part of the story (Table D4 in Appendix D). The relationship between firm level divergence and aggregate productivity growth is also economically significant: multiplying the coefficient estimate of -0.244 (Table 4, column 1) with the average pace of divergence – about 2.3 percentage point per year (from Figure 1, Panel B) –, we obtain that on average the divergence is associated with 0.6 percentage point lower productivity growth per year. Overall, these results imply that there is a sizable and robust negative relationship between the productivity divergence across firms and aggregate productivity growth during the 2000s.

4. The Role of Regulatory Policy

Some degree of MFP divergence across firms may be organic to the working of a market economy, particularly during the spreading phase of a general purpose technology such as ICT when experimentation looms large and it may be difficult for some firms to follow the best practice. Yet, the increase in the MFP gap, which is not uniform across sectors, is particularly pronounced in service sectors, and not only those related to ICT activities (Figure 3). Services are typically more sheltered from competitive pressures due to lower exposure to international competition and more stringent regulatory policies.

There are a number of channels through which pro-competitive product market reforms can strengthen the incentives for laggard firms to adopt frontier technologies, thereby moderating MFP divergence. Indeed, a range of firm-level evidence generally supports the idea that competitive pressures are a driver of productivity-enhancing innovation and adoption.[34] Building on these findings, we present evidence below that the rise in the MFP gap was less pronounced in sectors where the pace of product market reform was more intense.

4.1. Measuring product market reforms

To measure deregulations and pro-competitive reforms in product markets, we utilize a country-sector database on product market regulations (PMR). It is based on a detailed survey of government regulations collected by the OECD and has been used in academic contexts as a measure of anti-competitive regulation (e.g. Nicoletti and Scarpetta, 2003). The indicators derived from the answers are scaled on a range from 0 to 6, where higher values indicate more restrictive regulations.

The rationale of the PMR indicators is to capture the extent of "anti-competitive" regulations; that is, regulations "that inhibit competition in markets where competition is viable" (Conway and Nicoletti, 2003). The restrictions to competition captured by the PMR were defined either as barriers to access markets that are inherently competitive or as government interferences with market mechanisms in areas in which there are no obvious reasons why those should not be operating freely (e.g. price controls imposed in competitive industries as road freight or retail distribution). An important feature of these indicators is their *de jure* nature – i.e. they focus on rules and regulations as they appear in legislation. This is an advantage since it facilitates cross-

[34] *Inter alia*, see Nickell (1996); Blundell, Griffith and Van Reenen, (1999); Haskel, Pereira and Slaughter (2007).

country comparisons, but may come at the cost of effectively accounting for differences in implementation and enforcement across countries.

We exploit information on sector-specific regulation in 10 separate industries: 7 in network industries, 1 in retail, and 2 in professional services (see Conway and Nicoletti, 2006). Network industries include two energy sectors (electricity and gas), three transport sectors (road, rail and air) and two communication sectors (post and telecommunications). The two professional services industries refer to the business services sector (accounting and legal services) and the technical services sector (engineering and architecture services). The indicator captures different aspects of regulation, depending on the specific sector considered. For network industries, the indicator is largely about the organization of network access to potential service providers. For retail trade, it typically takes the form of entry barriers, specific restrictions for large firms and the flexibility of shops in terms of opening hours and prices. As for professional services, it focuses on barriers to entry and the way services are delivered and includes, amongst others, rules governing the recognition of qualifications and the determination of fees and prices.[35]

4.2. Empirical strategy

This section lays out the empirical strategy for testing whether PMR affects the productivity gap between frontier and non-frontier firms. We estimate the following baseline specification for the 10 market services sectors for which regulatory indicators are available over the period 1998-2013:[36]

$$\Delta^{ld} GAP_{cjt} = \beta \Delta^{ld} PMR_{cjt} + \gamma \Delta^{ld} E_{cjt} + \nu_c + \mu_s + \delta_{[c]t} + \varepsilon_{cjt} \tag{7}$$

[35] For retail and professional services industries, where the OECD PMR indicators are updated only every 5 years (1998, 2003, 2008, 2013), additional information was used on the timing of reforms. See details in Gal and Hijzen (2016) and in Appendix E.

[36] Throughout the analysis of PMR's impact on the productivity gap, the coverage is restricted to cases where the annual PMR indicators are available and where at least 10 firms are present in Orbis. The included 14 OECD countries are Austria, Belgium, Denmark, Finland, France, Germany, Italy, Japan, Korea, Portugal Slovenia, Spain, Sweden and the United Kingdom.

where Δ^{ld} denotes the long difference operator, corresponding to five years in the baseline specification;[37] GAP_{cjt} refers to the difference between the (unweighted) average MFP (MFPR or markup corrected MFPR) of global frontier firms and the (unweighted) average MFP of laggard firms in country c, industry j and year t.[38] PMR_{cjt} refers to the overall restrictiveness of product market regulation in key service industries (expressed in log terms),[39] which is increasing in the degree of regulation. Throughout the period analysed, there is a general decline in the restrictiveness of product market regulation ($\Delta^{ld}PMR_{cjt} < 0$) . Thus an estimated $\beta > 0$ implies that a slowdown in pro-competitive product market reforms (i.e. a smaller decline in PMR) is associated with a rising MFP gap between the global frontier and non-frontier firms.

The regression also includes the growth of sectoral employment (E) to control for both time-varying shocks within country*industry pairs and potential changes in the coverage of the dataset.[40] The baseline model includes separate country, industry and year fixed effects to control for omitted time-invariant country (ν_c) and industry (μ_j) trends (given the specification in long differences) – and common global shocks (δ_t). As an extension, we include interacted country-year fixed effects (δ_{ct}) to control for country-specific time-varying shocks (different trends and business cycles). To maximize the use of the data, we rely on overlapping five-year differences (e.g. 2013-2008, 2012-2007 etc.) but given that we cluster at the country-industry pair level this is innocuous (e.g. Bloom, Draca and Van Reenen, 2016). Finally, country-industry-year cells that contain less than 10 firms are excluded in order to reduce the influence of highly idiosyncratic firm-level developments.

One identification concern is that rigid services regulation might be a consequence, not a cause of the MFP gap between the global productivity frontier and non-frontier domestic firms. This would be the case if there were greater incentives for domestic firms to exert political

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[37] As discussed below, the significance of the results are not sensitive to the choice of the length of the long-differencing window.

[38] As robustness checks, the medians instead of the means will also be used.

[39] Taking the log of PMR is a useful transformation to the extent that it allows for reforms to be evaluated in relative terms, in relation to the pre-reform policy stance. This is particularly relevant as in many industries the strictness of regulation, as expressed by the PMR indicator, is already at low levels, and there is limited scope for further reforms that lead to a similar reduction in absolute terms in the indicator than in the past.

[40] The employment variable is based on information from the Orbis database, and is calculated as the average of log employment levels across firms.

pressures for raising anti-competitive regulations when the productivity gap is larger. Such lobbying activity by inefficient firms would upwardly bias the estimate of β. However, to the extent that MFP is pro-cyclical – and thus the gap from the global frontier is countercyclical –, and product market reforms are conducted when domestic economic conditions are weak (Bouis, Duval and Eugster, 2016), the estimated β would be biased in the opposite direction.

We adopt two additional identification strategies to confront the potential endogeneity of market regulation to economic conditions. In particular, we employ instrumental variables (IV) that exploit the existence of liberalization waves across countries and the role of external pressure in driving them (see Bouis, Duval and Eugster, 2016). Specifically, we utilize two instruments that are unlikely to be affected by sector-level economic outcomes in the country considered, and should not have any effect on GAP_{cjt} other than through pressure on domestic authorities to undertake reform. First, we rely on *"Reform pressure",* that is, the lagged level of market regulation, based on the idea that the scope for reform as well as the push to implement reform is larger the in country-sector pairs where the initial stance of product market regulation is stricter. Second, we also utilize the idea of *"Reform waves"* or *"Relative reform pressure"*, which we defined as reform activity in all other countries in the sample – as measured by the 5-year change in product market regulation in the given sector – to capture peer pressure from reforms in other countries. These peer pressures could arise due to competitiveness concerns by policymakers if they observe a restrictive regulatory framework in their country but a strong reform activity in others.

4.3. Results

Table 5 summarizes our main estimation results based on variants of equation (7) for the MFP gap based on MFPR and markup corrected MFP for the services sectors affected by product market regulation. As a starting specification, column 1 contains additive country, industry and year fixed effects, while starting from column 2, the regressions include instead country-year fixed effects to control for time varying country-specific shocks (e.g. business cycle effects) and separate industry fixed effects. Column 3 uses markup corrected MFP, while the last two columns instrument the regulatory reform, either by the initial stance of regulations (column 4) or by the average reform intensity in all other countries (column 5). In each case, the change in the MFP gap is positively and significantly related to the change in PMR. The IV estimates are larger in magnitude than the baseline estimates, although less precisely estimated, suggesting that weak sectoral performance may trigger market reforms, as opposed to lobbying for anti-competitive regulation. The results are robust to using alternative lengths of the long difference operator (Table E2 in the Appendix E) or the median (rather than mean) productivity of laggards to construct the MFP gap (Table E3).

The coefficient estimates in Column 1 of Table 5 and the descriptive statistics in Table D5 imply that a one standard deviation increase in PMR is associated with about one-third of a standard deviation increase in the MFP gap. To further illustrate the economic magnitude, we perform a simple counterfactual simulation that answers the question: how much the MFP gap would have risen if market reforms in five key services sectors had proceeded at the same pace of that observed in telecommunications, where reform was most extensive. Taking legal and accounting services as an example, we find that the MFP gap increased at an annual average rate of 3.8% over the sample period, and our estimates imply that 1.7 percentage points (45%) of this increase may have been avoided if liberalization in this sector had accelerated more rapidly. On average across the sectors analyzed, the divergence that is attributed to slow deregulation amounts to about 40%.

5. Conclusion

In this paper, we aimed to contribute to the debate on the global productivity slowdown – which has by and large been conducted from a macroeconomic perspective – from a more micro perspective. We provided new firm level evidence that highlights the importance of separately considering what happens to the frontier as well as to laggard (non-frontier) firms. The most striking feature of the productivity slowdown was found to be not so much a slowing in the rate of productivity growth at the global frontier, but rather a dynamic improvement of productivity at the global frontier coupled with an increasing productivity divergence between this frontier and the rest of the distribution. This productivity divergence remains after controlling for differences in capital deepening and markup behavior although there is evidence that market power of frontier firms has increased in services. This led us to suspect that the rising MFPR gap between global frontier and laggard firms may in fact reflect technological divergence. This may help reconcile views of *techno-optimists,* which emphasize the fast pace of technological innovations (probably pushed by frontier firms) with sluggish aggregate productivity figures, which are being held back by a slowing diffusion of these innovations or more generally business practices to the majority of (non-frontier) firms.

We also showed that this pattern of MFP divergence is happening while entrenchment at the top is increasing and entry and exit are slowing down. In addition, we report evidence that catch-up by laggards has also slowed down during the same period. Interestingly, the divergence is stronger in services and even more so in digital intensive sectors, where productivity divergence has also become apparent amongst the very top firms as well.

Digitalization can indeed contribute to rapid productivity gains at the global frontier, especially in knowledge intensive services, through reduced marginal costs and concomitant *winner-takes-all* dynamics. Yet, aggregate MFP growth was significantly slower in industries where MFP divergence was more pronounced, suggesting that the divergence observed is not solely driven by frontier firm pushing the boundary outward. In this regard, we contend that increasing MFP divergence – and the global productivity slowdown more generally – could reflect a slowdown in the technological diffusion process, as also confirmed by the slowing rate of catch-up. As suggested by recent theories, this could be a reflection of increasing adoption costs for laggards firms due to the increasing role of complementary intangible investments that modern technologies require (management, organizational changes, etc.). But it could also be symptomatic of rising entry barriers and a decline in the contestability of markets. Crucially, in both cases, there is scope for policy to alleviate the productivity slowdown.

Indeed, we found the rise in MFP divergence to be much more extreme in sectors where pro-competitive product market reforms were least extensive, suggesting that the observed rise in MFP divergence could be at least partly due to policy weakness stifling diffusion. Put differently, structural changes in the global economy meant that technological catch-up to the global productivity frontier became more difficult for the typical firm over the 2000s, but these difficulties were compounded by policy weakness. From this perspective, the opportunity cost of poorly designed product market regulations may have risen over time.

This research raises a number of issues for future research. First, it would be interesting to explore the impact of the crisis and macroeconomic policies on global frontier and laggard firms, via the channels identified in Anzoategui et al (*forthcoming*) and Gopinath et al (2017). Second, containing MFP divergence may carry a double-dividend both for productivity and equity, given the positive correlation between wages and productivity across firms, and to the extent that the observed rise in wage inequality is closely related to cross-firm inequality in firm-average wages (Song et al, 2018).

Table 1

Firm characteristics: firms at the frontier vs. below the frontier

A: Labor productivity based frontier definition

Sector	Manufacturing			Services		
Frontier status	Below frontier	At the frontier		Below frontier	At the frontier	
Variable	Mean st.dev.	Mean st.dev.	Sign. diff.	Mean st.dev.	Mean st.dev.	Sign. diff.
Productivity	10.7	12.0	***	12.0	11.9	***
	(0.6)	*(0.4)*		*(0.7)*	*(0.7)*	
Employees	49.3	45.1	***	59.5	38.0	***
	(52.1)	*(33.8)*		*(156.6)*	*(24.8)*	
Capital-labour ratio [1]	86.1	274.5	***	12.5	49.4	***
	(115.3)	*(425.5)*		*(32)*	*(169.2)*	
Revenues [2]	11.8	39.0	***	1.1	3.8	***
	(21.6)	*(58.8)*		*(2.2)*	*(9.2)*	
Markup (log)	0.05	0.10	***	0.07	0.26	***
	(0.4)	*(0.4)*		*(0.4)*	*(0.5)*	
Wages [1]	31.0	49.4	***	12.3	27.1	***
	(15.1)	*(18.2)*		*(20)*	*(37.9)*	
Number of firms	21,191	825		22,053	627	

B: MFP based frontier definition

Sector	Manufacturing			Services		
Frontier status	Below frontier	At the frontier		Below frontier	At the frontier	
Variable	Mean st.dev.	Mean st.dev.	Sign. diff.	Mean st.dev.	Mean st.dev.	Sign. diff.
Productivity	10.4	11.6	***	11.6	11.7	***
	(0.6)	*(0.4)*		*(0.7)*	*(0.7)*	
Employees	48.3	73.7	***	59.1	53.4	
	(46.8)	*(126)*		*(155.3)*	*(115.6)*	
Capital-labour ratio [1]	89.3	214.3	***	12.7	16.5	***
	(125.1)	*(406)*		*(32.6)*	*(75.6)*	
Revenues [2]	11.5	50.5	***	1.1	5.1	***
	(19.9)	*(74.1)*		*(2.2)*	*(13.1)*	
Markup (log)	0.05	0.04		0.07	0.20	***
	(0.4)	*(0.4)*		*(0.4)*	*(0.5)*	
Wages [1]	31.0	51.0	***	12.3	27.6	***
	(15.1)	*(17.1)*		*(20)*	*(37.7)*	
Number of firms	21,317	706		22,147	538	

Notes: Productivity is measured in logs, and productivity denotes the measure mentioned in the panel titles (labor productivity, MFP for panel A and B, respectively). In 2013. See details in Section 1 for the calculation of the frontier and the productivity measures. Notation for p-values: *** p<0.01, ** p<0.05, * p<0.1

[1]: in thousands of 2005 USD; [2]: in millions of 2005 USD; both using PPP conversions.

Table 2

The frontier is growing significantly faster than the rest, more strongly in services and especially data services

Productivity measure as dependent variable	Labour productivity	MFP	Markup corrected MFP
Explanatory variables	(1)	(2)	(3)
Trend	0.009*	0.008*	0.011**
	(0.004)	*(0.005)*	*(0.005)*
Frontier X Trend	0.019***	0.020***	0.018***
	(0.004)	*(0.005)*	*(0.005)*
Services X Trend	-0.012**	-0.011**	-0.015**
	(0.004)	*(0.005)*	*(0.005)*
Services X Frontier X Trend	0.011**	0.009**	0.008*
	(0.004)	*(0.005)*	*(0.005)*
Data Services X Trend	0.021***	0.021***	0.021***
	(0.004)	*(0.005)*	*(0.005)*
Data Services X Frontier X Trend	0.030***	0.026***	0.024***
	(0.004)	*(0.005)*	*(0.005)*
R-squared	0.370	0.496	0.306
Industry X Frontier status FEs	Yes	Yes	Yes
Observations	870,141	870,588	870,588

Notes: The dependent variable is the level of log-productivity, and the frontier status is defined as being in the top 5% of the productivity distribution, within each industry and year. See equation (3) for the exact formulation. Standard errors (in parentheses) are clustered at the industry level. Notation for p-values: *** p<0.01, ** p<0.05, * p<0.1

Table 3

The top of the distribution is diverging faster in services, especially in data services

Sectors	Manufacturing		Services		Data services	
Productivity measures	Labour productivity	MFP	Labour productivity	MFP	Labour productivity	MFP
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
trend	0.008*	0.008	-0.003	-0.002	0.018***	0.018***
	(0.005)	*(0.005)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Top10% X trend	0.017***	0.019***	0.025***	0.025***	0.050***	0.044***
	(0.002)	*(0.002)*	*(0.003)*	*(0.003)*	*(0.004)*	*(0.003)*
Top5% X trend	0.001*	0.001	0.003	0.002*	-0.003	0.002
	(0.001)	*(0.001)*	*(0.002)*	*(0.001)*	*(0.003)*	*(0.005)*
Top2% X trend	0.002	0.000	0.005**	0.003**	0.034***	0.022**
	(0.002)	*(0.002)*	*(0.002)*	*(0.001)*	*(0.009)*	*(0.009)*
Industry X frontier status FEs	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.380	0.446	0.496	0.631	0.356	0.351
Observations	385,504	385,644	484,637	484,944	3,137	3,138

Note: The dependent variable is the level of log-productivity, and the frontier is defined as described in the main text. See equation (4) for the exact formulation. Standard errors (in parentheses) are clustered at the industry level. Notation for p-values: *** p<0.01, ** p<0.05, * p<0.1

Table 4

Productivity divergence and aggregate productivity growth: a negative relationship

Aggregate productivity regressed on the productivity gap (long-differences over 5 years)

Dependent variable: aggregate productivity measure	Δ MFP		Δ Labour productivity	
Productivity gap measure variant:	Mean	Median	Mean	Median
Explanatory variable	(1)	(2)	(3)	(4)
Δ Productivity gap	-0.244***	-0.273***	-0.227**	-0.256***
	(0.090)	*(0.068)*	*(0.097)*	*(0.080)*
R-squared	0.681	0.698	0.558	0.571
Industry and year fixed effects	Yes	Yes	Yes	Yes
Observations	432	432	432	432

Notes: All variables are measured in log differences over overlapping five-years. Standard errors are clustered at the industry level. The productivity gap is defined using firm-level MFP (Wooldridge, 2009, methodology) and is calculated as the difference in mean productivity at and below the frontier (columns 1 and 3) or as the difference in median productivity in the two segments of firms (columns 2 and 4). The frontier is defined as the set of firms with the top 5% productivity level within each detailed industry and in each year (see details in Section 1). The sample covers 54 industries and 23 countries over 2001-2013 (see details in Appendix D). Notation for p-values: *** p<0.01, ** p<0.05, * p<0.1

Table 5

Product market reforms and productivity divergence

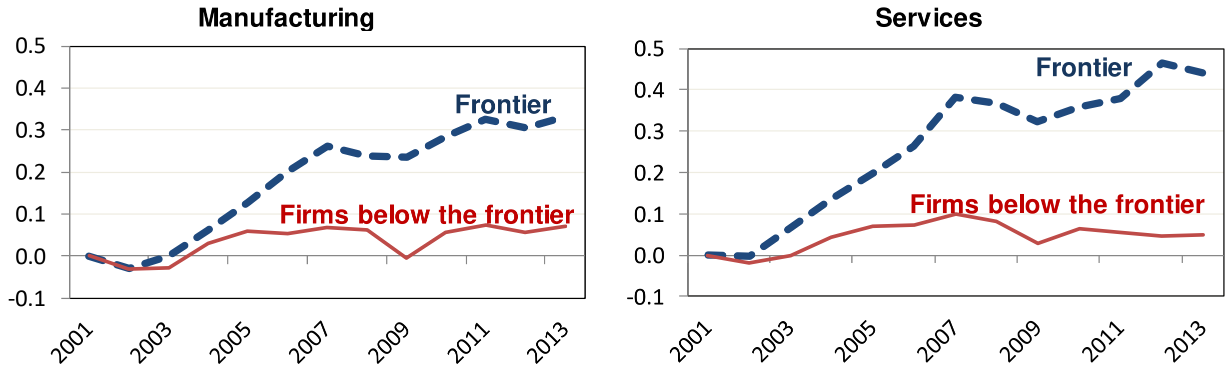
Dependent variable:	Δ MFP gap		Δ Mark-up corrected MFP gap	Δ MFP gap	
Estimation method:	OLS	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)
Δ Product Market Regulation$_{s,c,t}$	0.205***	0.231***	0.311**	0.338*	0.676***
	(0.065)	*(0.083)*	*(0.132)*	*(0.194)*	*(0.179)*
Industry fixed effects	YES	YES	YES	YES	YES
Country fixed effects	YES	NO	NO	NO	NO
Year fixed effects	YES	NO	NO	NO	NO
Country X year fixed effects	NO	YES	YES	YES	YES
R-squared	0.201	0.323	0.463	0.318	0.235
Observations	458	458	376	458	458

Note: Regression results based on equation (7). Cluster robust standard errors (at the country-industry level) are in parentheses. Notation for p-values: *** p<0.01, ** p<0.05, * p<0.1Both the MFP gap and the PMR indicator are measured in log terms. The MFP gap is calculated at the country-industry-year level, by taking the difference between the global frontier and the unweighted average of log productivity of non-frontier firms. The time period is 1998-2013. In column 4, ΔPMR (denoting a five-year difference in PMR) is instrumented by the lagged level of PMR (in t-5), while in column 5, ΔPMR for a given country is instrumented by the average 5-year change in PMR in the given sector across all other countries in the sample. The instrumental variable is highly significant with the expected signs in the first-stage equation.

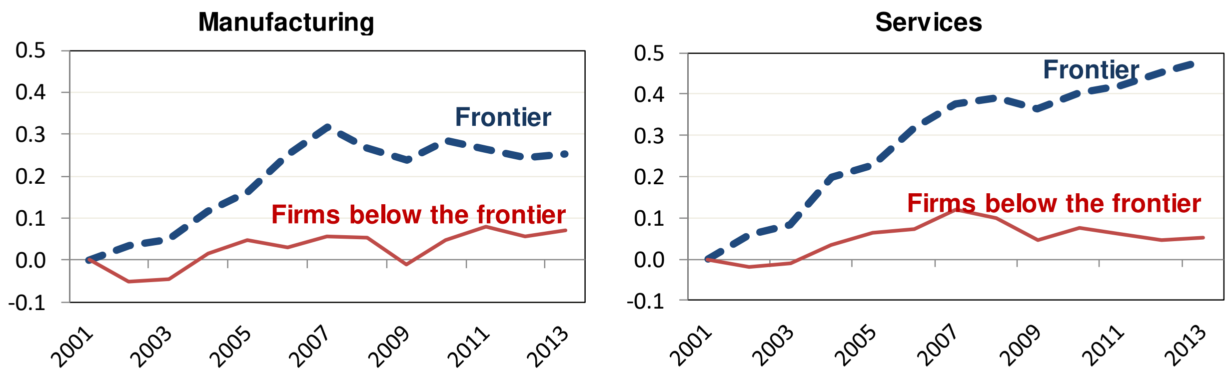
Figure 1

Divergence between the frontier and the rest

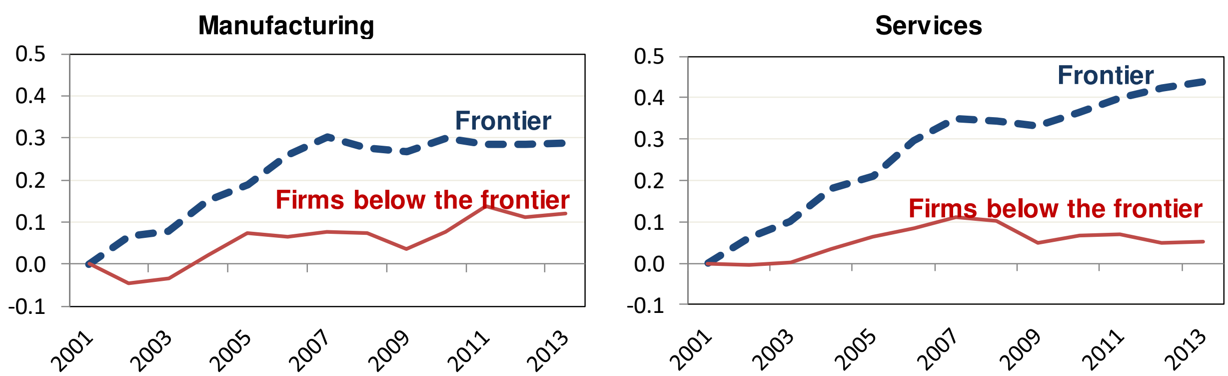
A: Labor productivity



B: Multi-factor productivity (MFP)



C: Markup corrected MFP

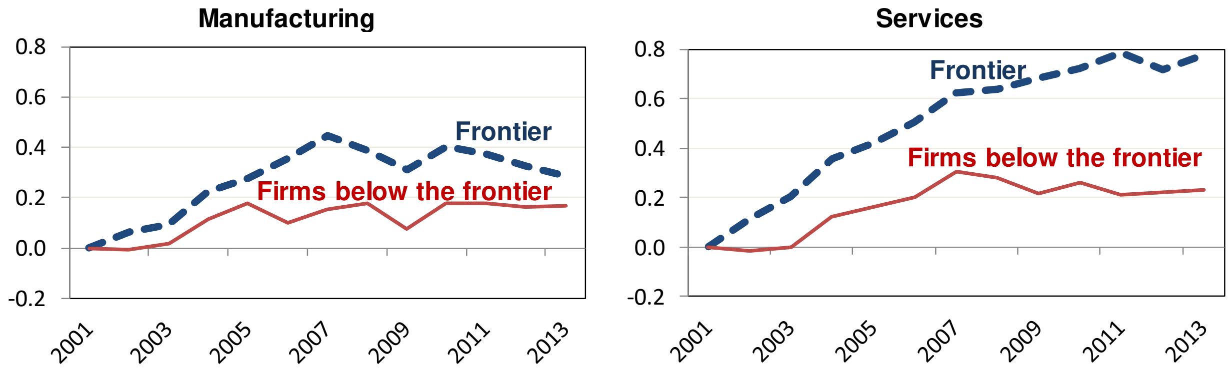


Note: The global frontier is measured by the average of log productivity for the top 5% of companies with the highest productivity levels within each two-digit industry. Firms below the frontier capture the average log productivity of all the other firms. Unweighted averages across two-digit industries are shown for manufacturing and services, normalized to 0 in the starting year. The time period is 2001-2013. The vertical axes represent log-point differences from the starting year: for instance, the frontier in manufacturing has a value of about 0.3 in the final year, which corresponds to approximately 30% higher in productivity in 2013 compared to 2001. Services refer to non-financial business sector services.

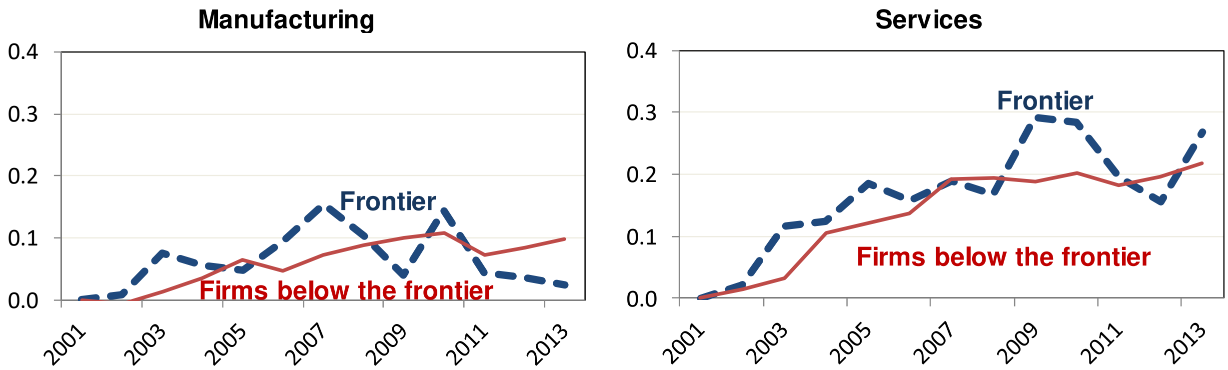
Figure 2

Is the frontier getting bigger?

A: Divergence in revenues



B: No divergence in employment

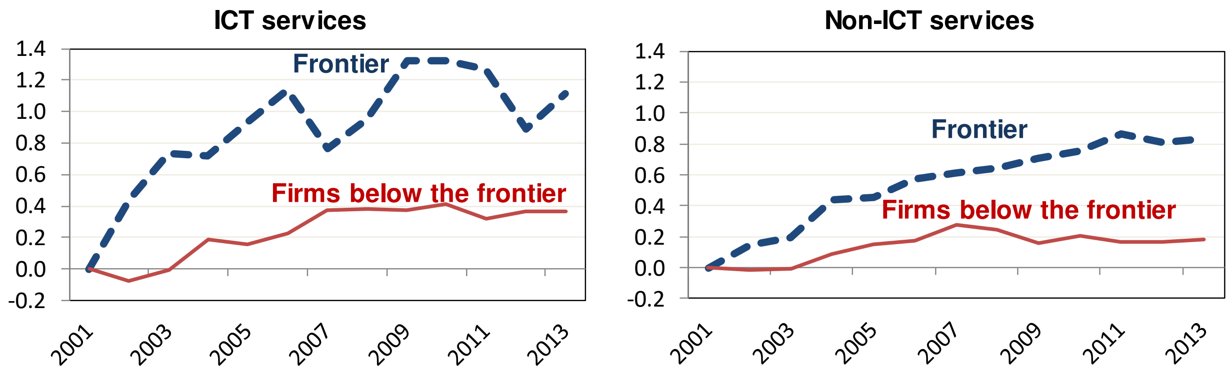


Note: the global frontier group of firms is defined by the top 5% of companies with the highest productivity levels, measured by markup corrected MFPR within each two-digit industry. Laggards capture all the other firms. Unweighted averages across two-digit industries are shown for log revenues and log employment, for Panels A and B, respectively, separately for manufacturing and services, normalized to 0 in the starting year. MFPR uses the Wooldridge (2009) methodology based production function estimation, while the markup estimation used for corrected MFPR uses the De Loecker and Warzynski (2012) methodology. Time period is 2001-2013. Services refer to non-financial business services.

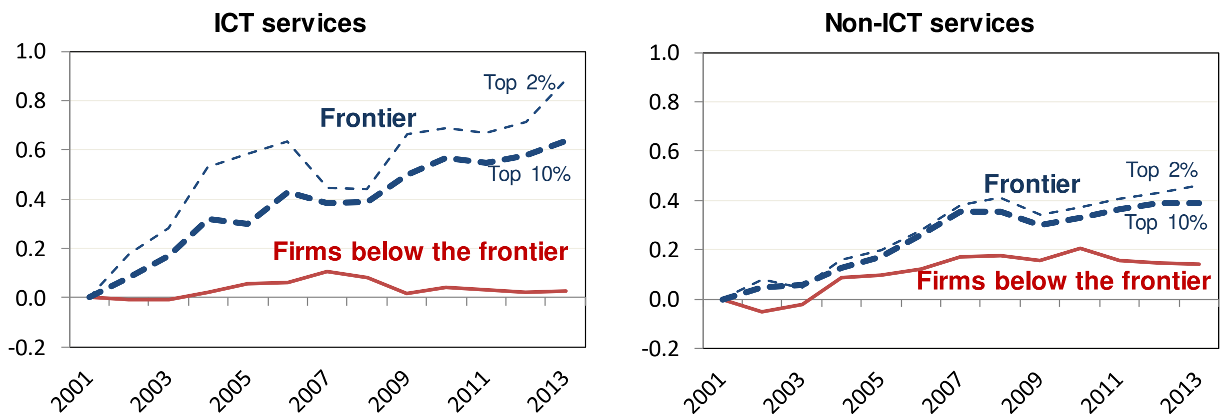
Figure 3

Evidence on "Winner-takes-all" dynamics

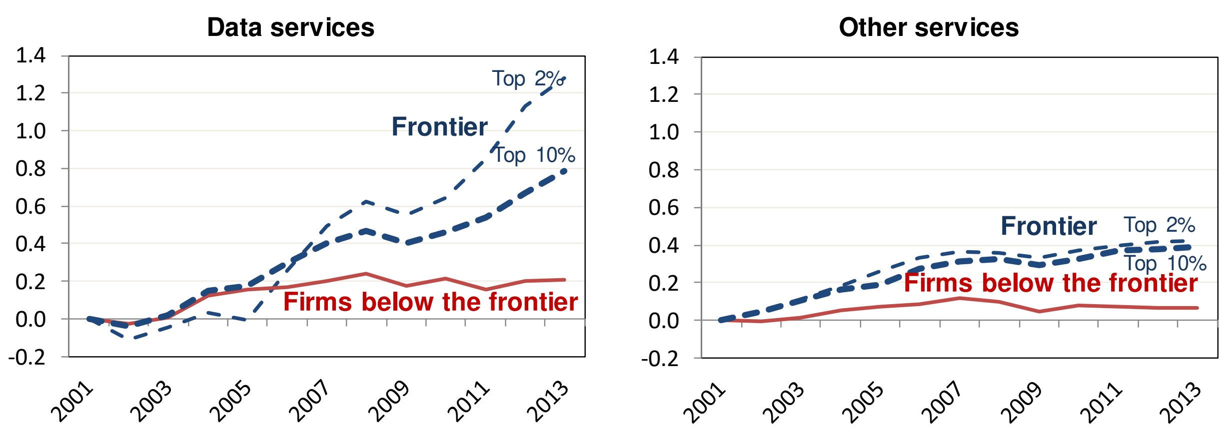
A: Divergence in revenues, especially in ICT services



B: Divergence in MFP: stronger in ICT services, especially within the top



C: Divergence in MFP: especially strong in data services, more so at the very top

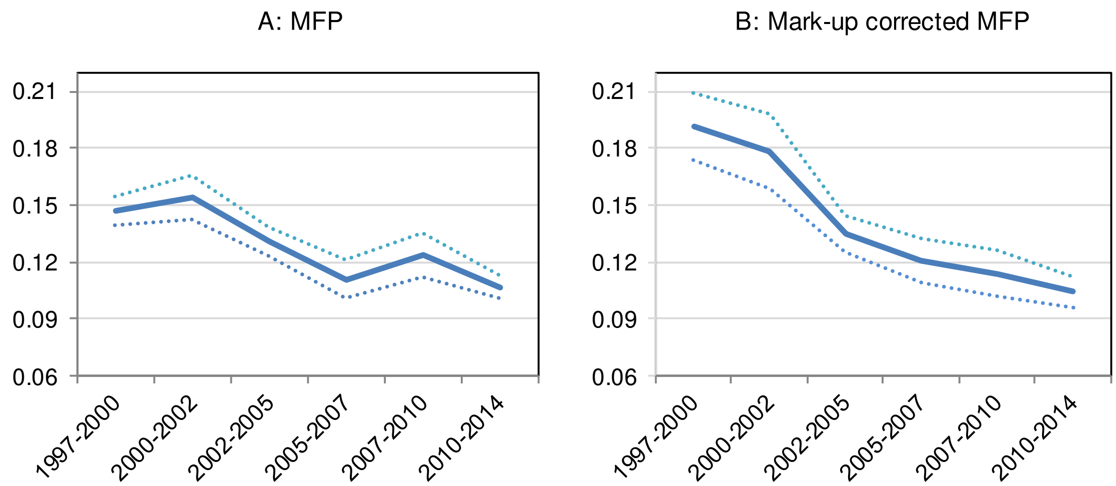


Notes: ICT services refer to the "Information and communication" sector (industry code J in NACE Rev. 2) and "Postal and courier activities" (53). Data services refer to the "Information service activities" sector (63). For more details see the notes of Figure 1. Since the figures are depicted as within-sector differences, the evolution of revenues can be interpreted as changes in the relative market shares for frontier and other firms.

Figure 4

The pace of convergence slowed, especially before the crisis

Estimated convergence parameters by time-periods

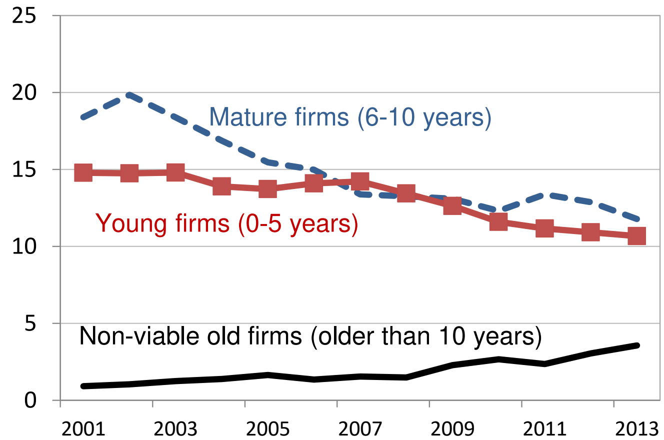


Note: The lines show the evolution over time of the estimated δ_k coefficient from the firm level MFP growth regression (equation (5)), presented in Table C1 of Appendix C (Column 1), while the dashed lines provide the 95% confidence interval around these coefficient estimates.

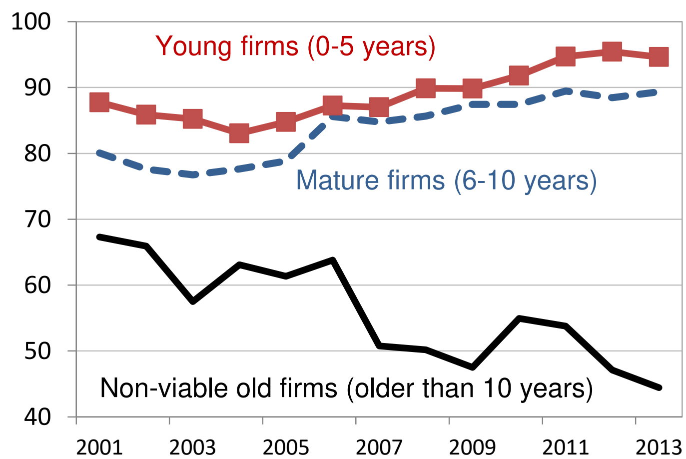
Figure 5

Indicators of declining market dynamism amongst firms below the frontier

A: The share different types (in % of the total sample)



B: Relative MFP levels of different types of firms (in %; old viable firms = 100%)



Note: The figures show the shares (panel A) and the relative productivity (panel B) of three groups of firms: firms aged 5 years or less (young firms), firms aged 6 to 10 years (mature firms) and firms older than 10 years that record negative profits over at least two consecutive years (non-viable old firms). The omitted group are firms older than 10 years that do not record negative profits over at least two consecutive years (viable old firms). The age of the firm is calculated using the incorporation date as recorded in the database. The estimates are unweighted averages across industries in the non-farm non-financial business sector.

Appendix A: Firm-level Productivity Divergence: Robustness

This Appendix presents a series of robustness checks for the diverging pattern of firm-level productivity across the most productive and other firms.

Table A1

Robustness of divergence regressions to variations in the definition of the frontier

A. Variable number of firms at the frontier

Productivity measure as dependent variable	Labour productivity	MFP	Markup corrected MFP
Explanatory variables	(1)	(2)	(3)
Trend	0.008*	0.008	0.010**
	(0.004)	*(0.005)*	*(0.005)*
Frontier X Trend	0.014***	0.015***	0.014***
	(0.002)	*(0.003)*	*(0.003)*
Services X Trend	-0.013**	-0.012**	-0.016***
	(0.006)	*(0.006)*	*(0.006)*
Services X Frontier X Trend	-0.000	-0.000	0.000
	(0.004)	*(0.004)*	*(0.005)*
Data Services X Trend	0.020***	0.020***	0.021***
	(0.003)	*(0.003)*	*(0.003)*
Data Services X Frontier X Trend	0.028***	0.024***	0.017***
	(0.003)	*(0.003)*	*(0.003)*
R-squared	0.371	0.497	0.306
Industry X Frontier status FEs	Yes	Yes	Yes
Observations	870,141	870,588	870,588

B. Smoothed firm-level productivity measures (using a 3-year moving average)

Productivity measure as dependent variable	Labour productivity	MFP	Markup corrected MFP
Explanatory variables	(1)	(2)	(3)
Trend	0.003	0.001	0.003
	(0.004)	*(0.004)*	*(0.004)*
Frontier X Trend	0.024***	0.025***	0.025***
	(0.002)	*(0.002)*	*(0.002)*
Services X Trend	-0.007	-0.006	-0.008
	(0.005)	*(0.005)*	*(0.005)*
Services X Frontier X Trend	0.010**	0.007	0.004
	(0.005)	*(0.005)*	*(0.004)*
Data Services X Trend	0.015***	0.016***	0.018***
	(0.004)	*(0.003)*	*(0.003)*
Data Services X Frontier X Trend	0.043***	0.033***	0.028***
	(0.004)	*(0.004)*	*(0.003)*
R-squared	0.403	0.544	0.347
Industry X Frontier status FEs	Yes	Yes	Yes
Observations	521,868	522,113	522,113

Notes: The dependent variable is the level of log-productivity, and the frontier is defined as described in the main text, with the following exceptions: in Panel A the number of firms in the top 5% group varies with the sample and not fixed over time, in Panel B, productivity is replaced by its 3-year moving average. See equation (3) for the exact formulation in Section IV. Standard errors (in parentheses) are clustered at the 2-digit industry level. *** p<0.01, ** p<0.05, * p<0.1

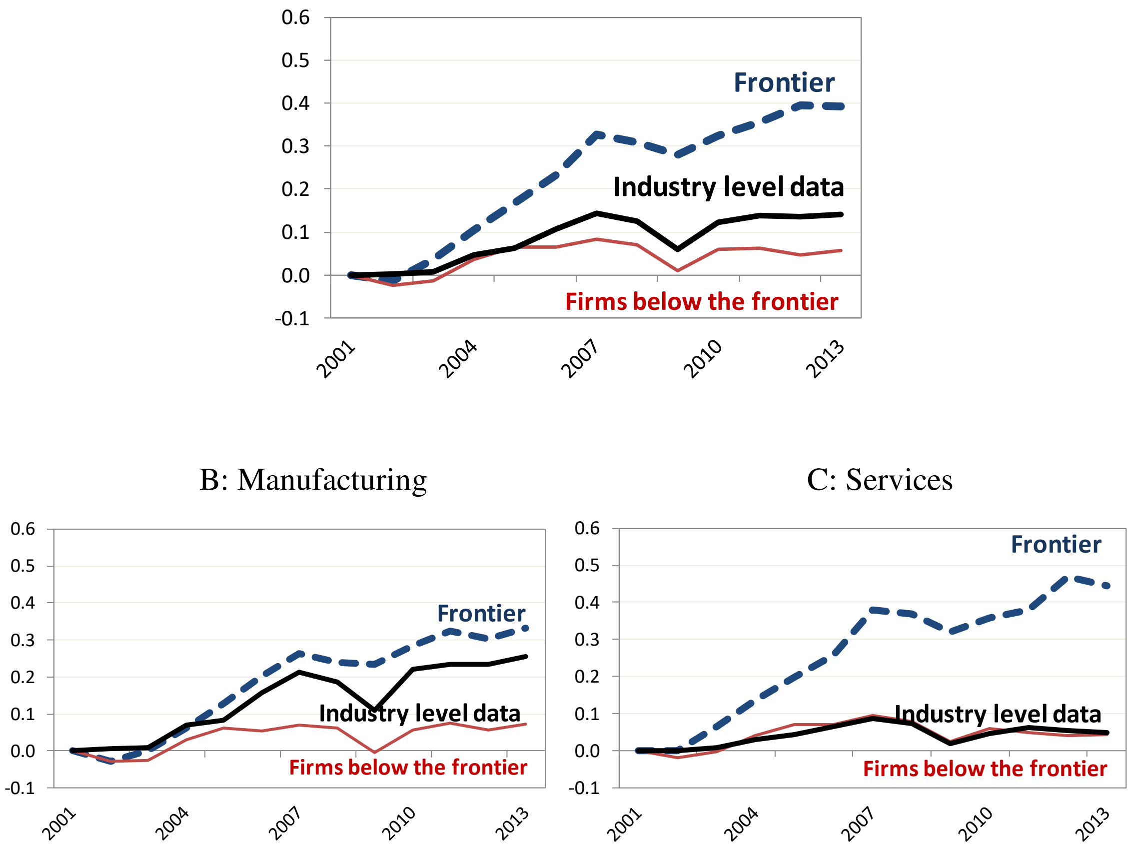
Figure A1

Divergence: firm-level patterns vs industry aggregate productivity from national accounts

A: Business Sector

B: Manufacturing

C: Services

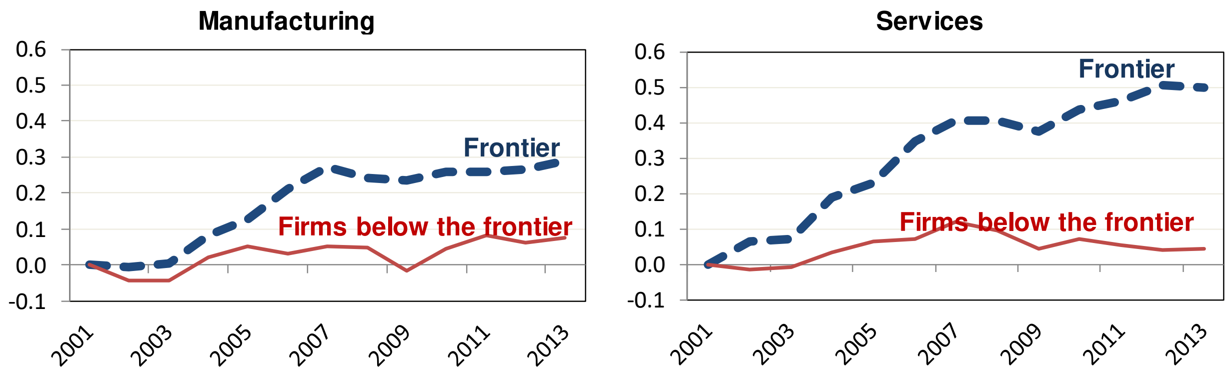


Notes: The global frontier is measured by the average of log labor productivity (value added over employees) for the top 5% of companies with the highest productivity levels within each two-digit industry. Laggards capture the average log productivity of all the other firms. Unweighted averages across two-digit industries are shown for manufacturing and services, normalized to 0 in the starting year. Services refer to non-financial, non-real estate business services (industry codes 45-82, excluding 64-68, in NACE Rev.2.). The business sector denotes manufacturing and services. The sectoral data refers to aggregate log labor productivity (value added over total employment), averaged across countries and industries at the two-digit detail (unweighted). In cases the two-digit details are not available, higher level industry groups are used. The industry level aggregates are employment weighted averages of all companies and self-employed businesses within the two-digit industries, whereas the firm-level information is an unweighted average of companies with at least 20 employees.

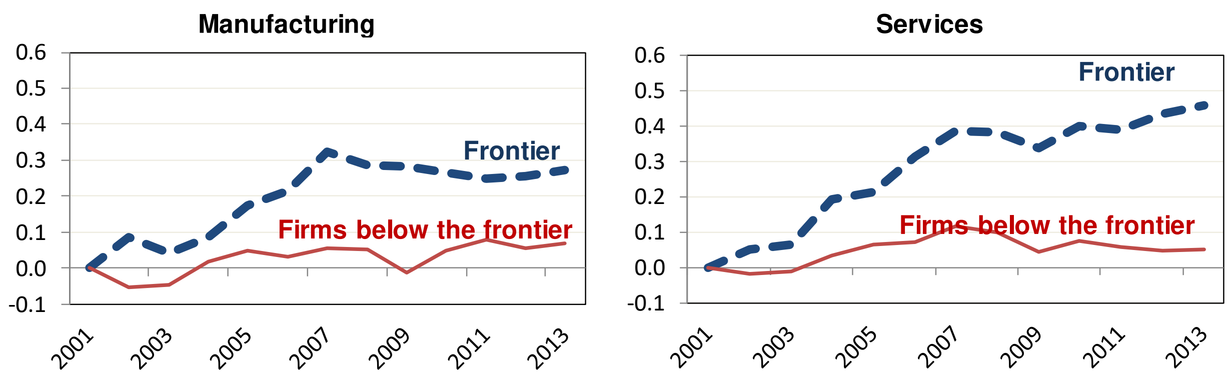
Figure A2

Divergence: decomposing the labor productivity frontier by MFPR and capital intensity

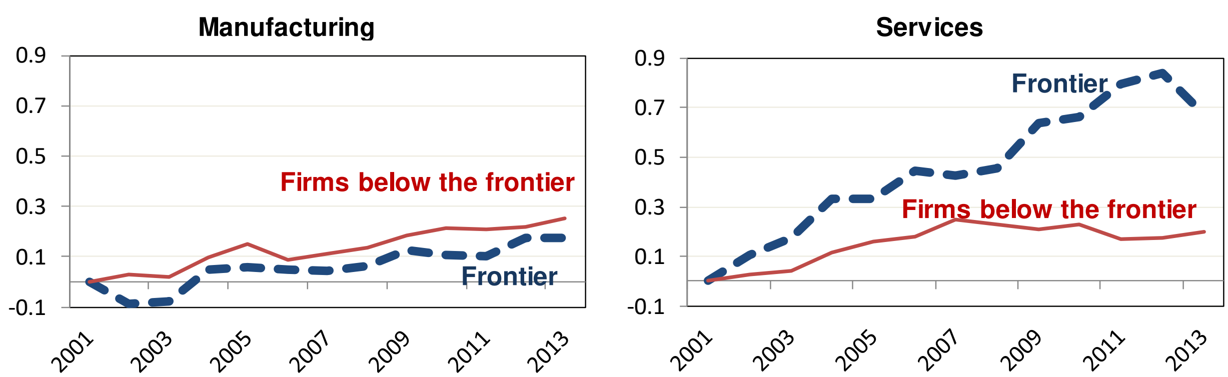
A: Labor productivity*



B: MFPR



C: Capital intensity (K/L)

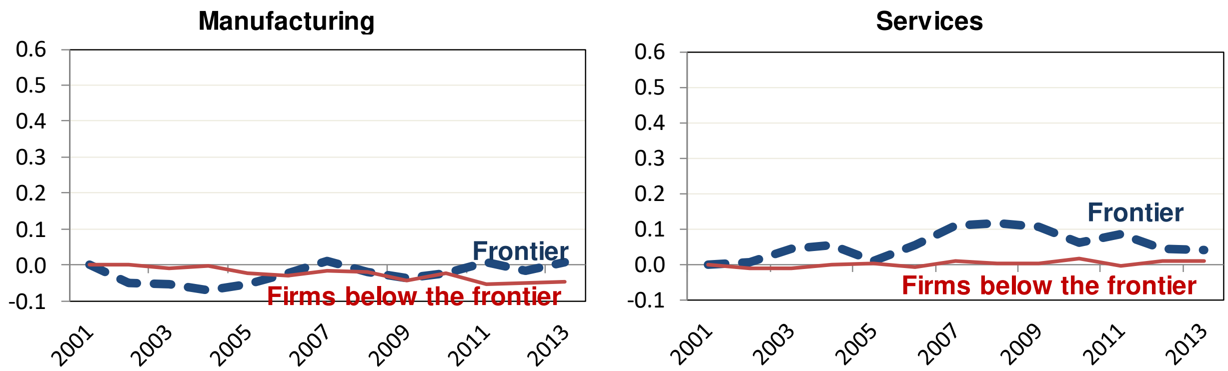


Notes: The frontier and non-frontier groups are based on labor productivity. Unweighted averages across two-digit industries are shown for the Wooldridge (2009) type production-function based log MFPR measure and the log of real capital stock over employment for Panels A and B, respectively, separately for manufacturing and services, normalized to 0 in the starting year. Time period is 2001-2013. The sample is restricted to those companies that have data available to measure capital stock and MFP. *Labor productivity is repeating that of Figure A2 but restricted to a common sample with MFPR and capital intensity.

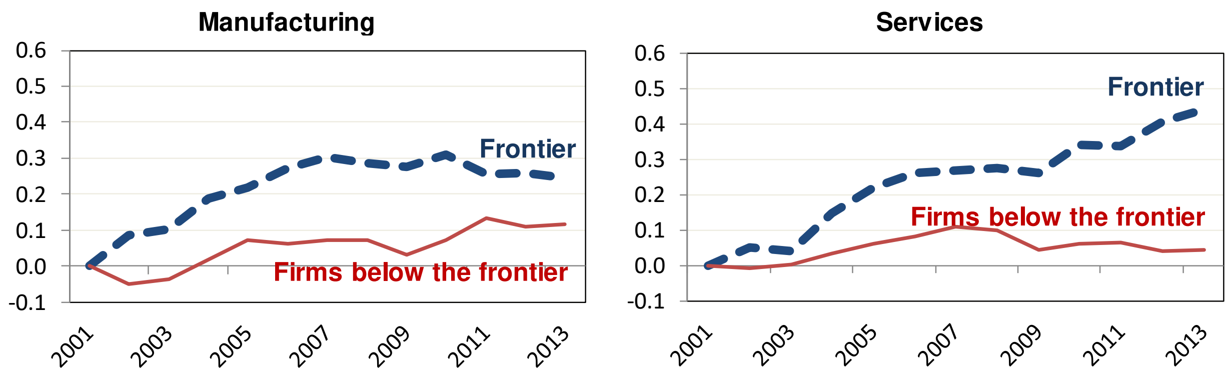
Figure A3

Divergence: decomposing the MFPR frontier by markups and markup corrected MFPR

A: Markups



B: Markup corrected MFPR

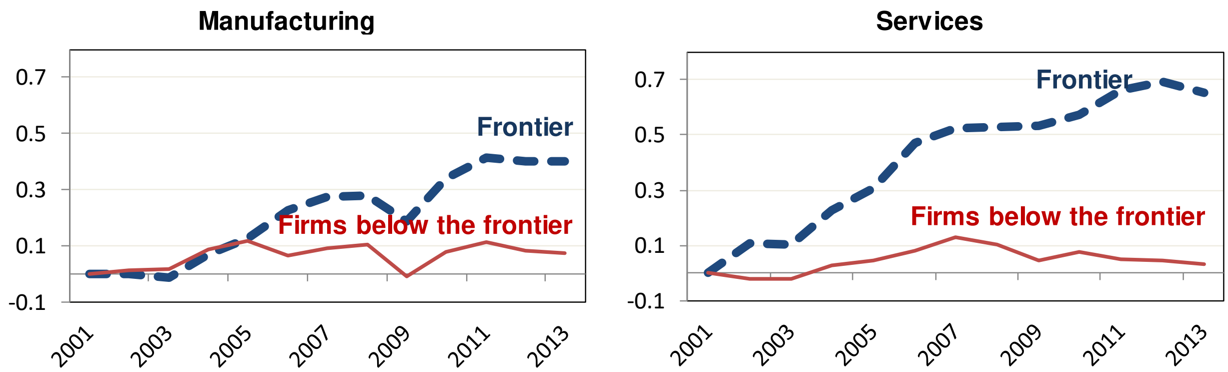


Notes: The frontier and non-frontier groups are based on MFPR (Wooldridge, 2009) productivity. Unweighted averages across two-digit industries are shown for the log of markups (De Loecker and Warzynski, 2012) based on employment as variable input (Panel A). Markup corrected MFPR is shown in Panel B, and is defined as the difference between MFPR and markups (both measured in logs; see Section 1). Time period is 2001-2013.

Figure A4

Divergence: alternative labor productivity definition

Labor productivity: operating revenues per worker

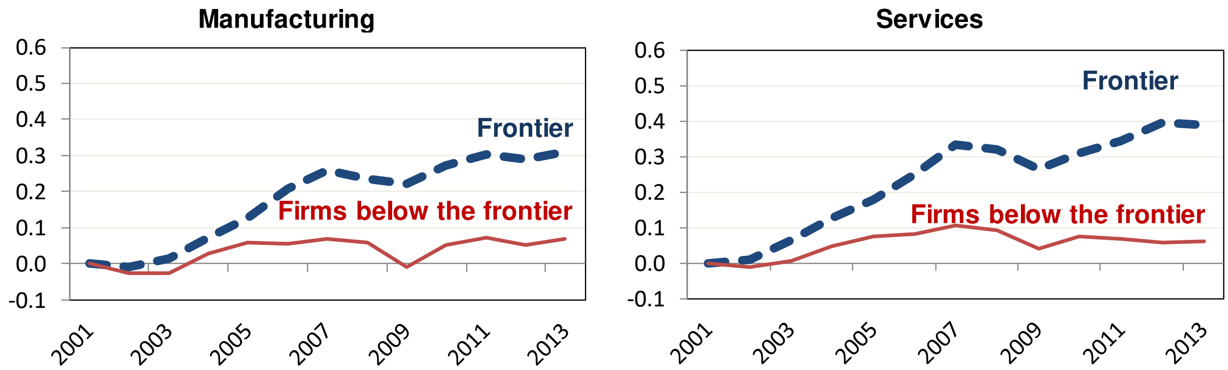


Notes: The global frontier is measured by the average of log labor productivity (measured as revenue per worker) for the top 5% of companies with the highest productivity levels within each two-digit industry. Laggards capture the average log productivity of all the other firms. Unweighted averages across two-digit industries are shown for manufacturing and services, normalized to 0 in the starting year. Services refer to non-financial business services. Time period is 2001-2013.

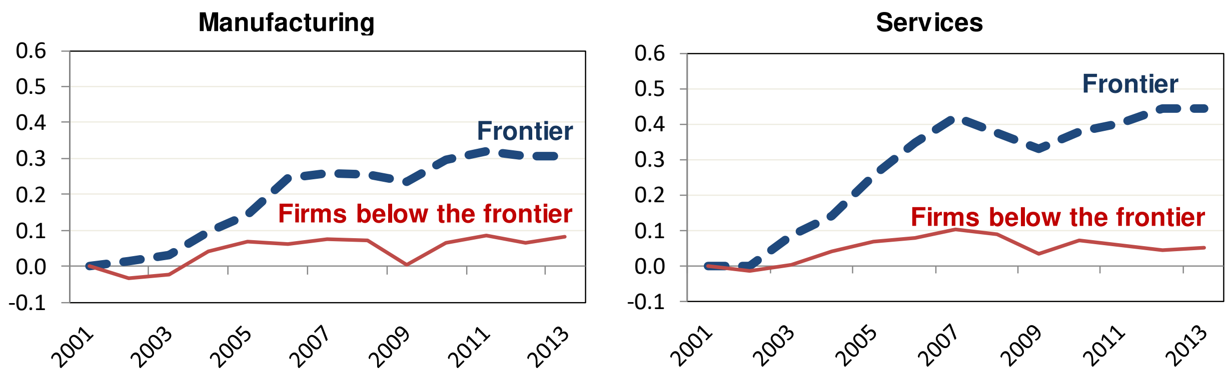
Figure A5

Divergence: alternative frontier definitions

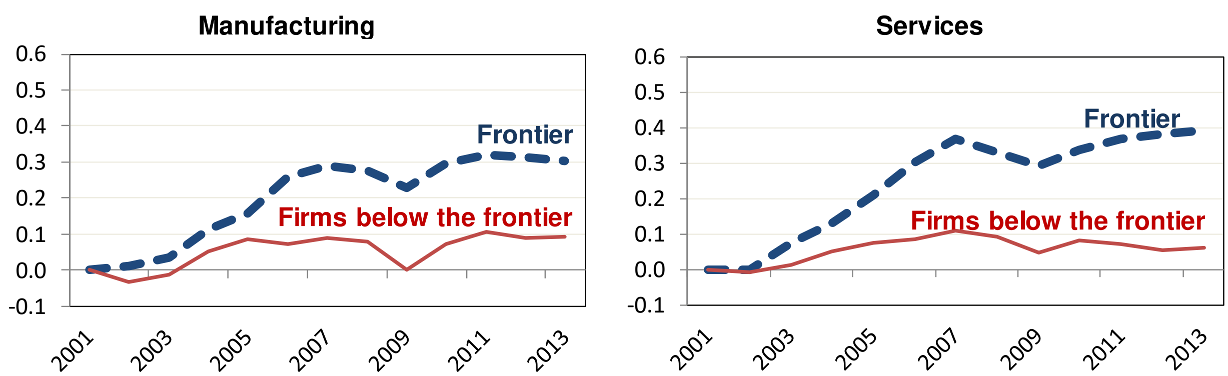
A: Frontier – 10% most productive firms within each sector



B: Frontier – 50 most productive firms within each sector



C: Frontier – 100 most productive firms within each sector

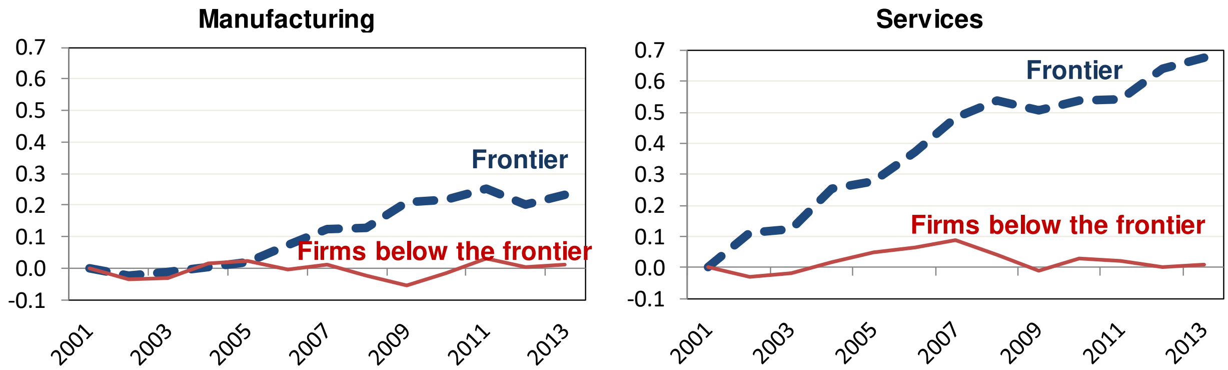


Notes: The global frontier is measured by the average of log labor productivity (value added per worker) for the top 10% of, top 50 and top 100 companies with the highest productivity levels within each two-digit industry, in Panel A, B and C, respectively. Laggards capture the average log productivity of all the other firms. Unweighted averages across two-digit industries are shown for manufacturing and services, normalized to 0 in the starting year. Services refer to non-financial business services. Time period is 2001-2013.

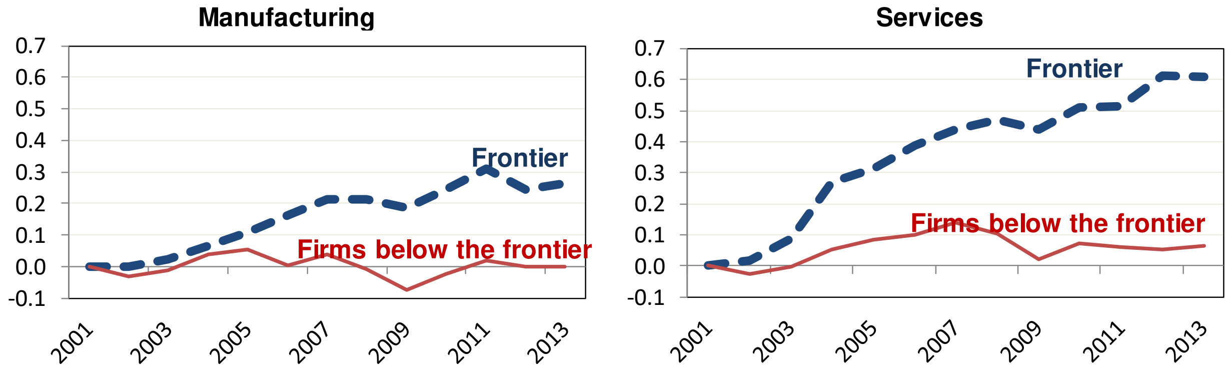
Figure A6

Divergence: excluding subsidiaries that are part of a group

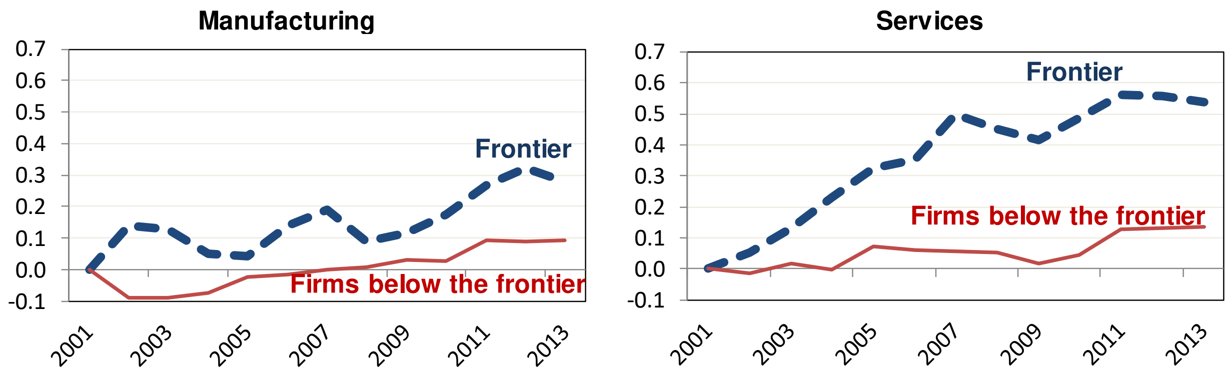
A: Labor productivity: value added per worker



B: MFPR



C: Markup corrected MFPR

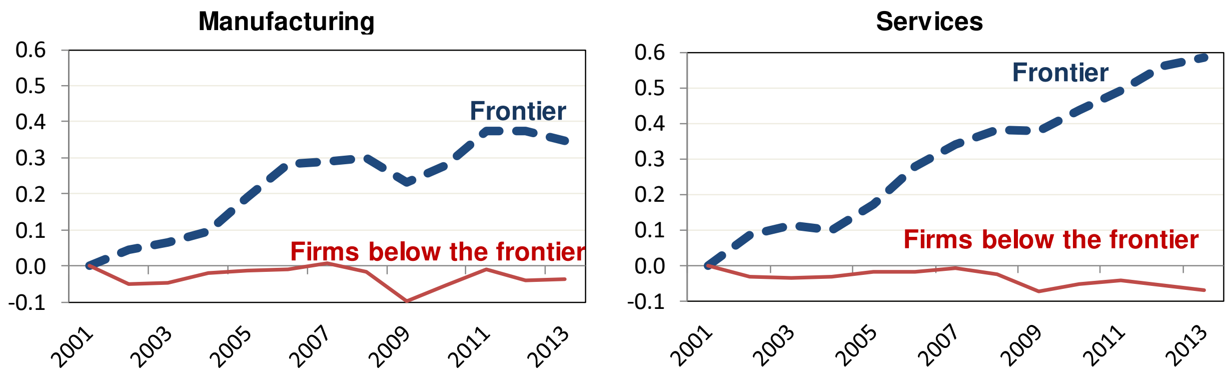


Notes: See notes below Figure 1. These figures retain only the consolidated accounts of the ultimate owners (headquarters) of groups or standalone firms that are not part of any group. Firms with an unknown status are omitted, leading to a substantial reduction in sample size. The available ownership link structure in Orbis may not be complete, especially for earlier years. Time period is 2001-2013.

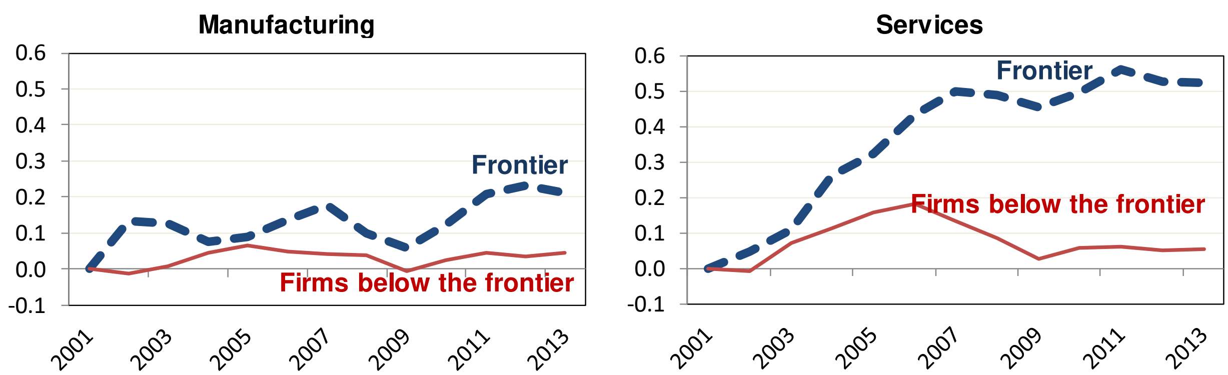
Figure A7

Divergence: alternative MFPR definitions

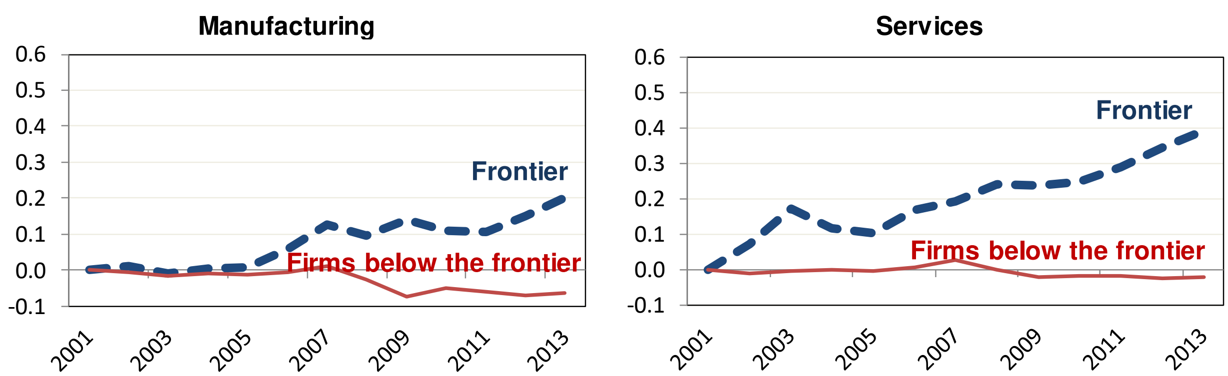
A: MFP – Solow



B: MFPR – Wooldridge (2009) gross-output based production function



C: MFPR – Wooldridge (2009) labor costs as labor inputs in the production function

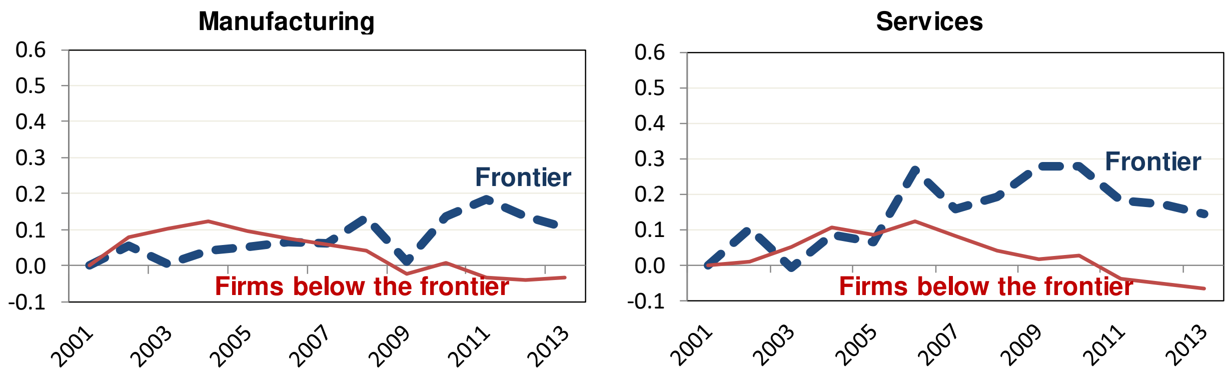


Notes: The global frontier is measured by the average of the log of an index-number based Solow residual MFP measure (using OECD National Accounts wage shares and assuming constant returns to scale; Panel A); a residual from a gross-output based Wooldridge (2009) production function estimation (Panel B); using labor costs as labor inputs in our baseline Wooldridge (2009) production function approach to capture changing labor quality and hours worked. For all of these measures, the top 5% of companies with the highest MFP levels within each two-digit industry is defined as the frontier. Laggards capture the average log productivity of all the other firms. Unweighted averages across two-digit industries are shown for manufacturing and services, normalized to 0 in the starting year. Services refer to non-financial business services. Time period is 2001-2013.

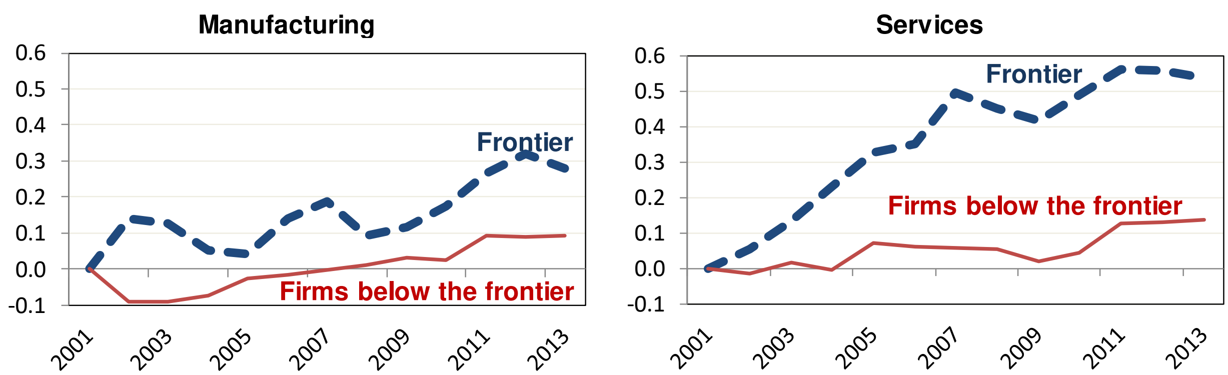
Figure A8

Divergence: markup corrected MFP using materials as flexible inputs

A: Markup



B: Markup corrected MFPR

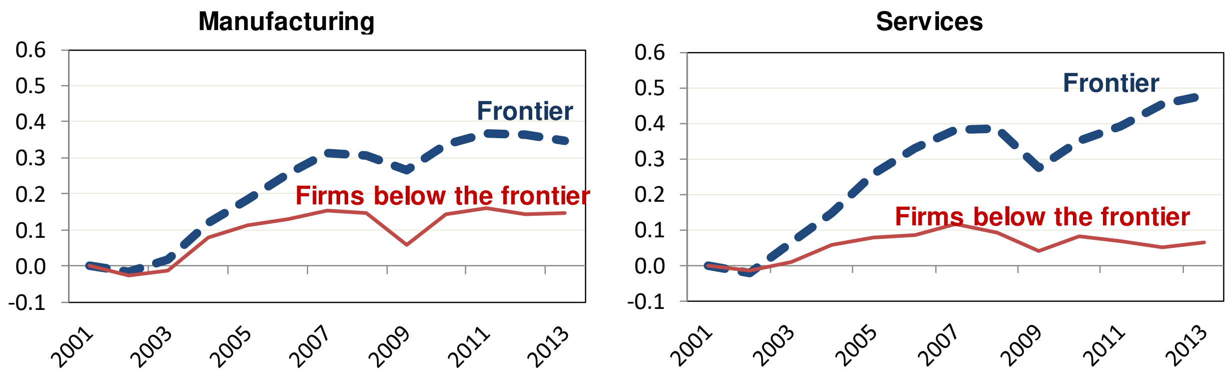


Notes: The global frontier is measured by top 5% of companies with the highest Wooldridge (2009) production function estimation based productivity levels (MFPR) within each two-digit industry. Laggards capture the average log productivity of all the other firms. Panel A shows the average level of (log) markups and Panel B the average level of markup corrected MFPR for these two groups. The markup estimation uses the De Loecker and Warzynski (2012) methodology. Unweighted averages across two-digit industries are shown for manufacturing and services, normalized to 0 in the starting year. Services refer to non-financial business services. Time period is 2001-2013.

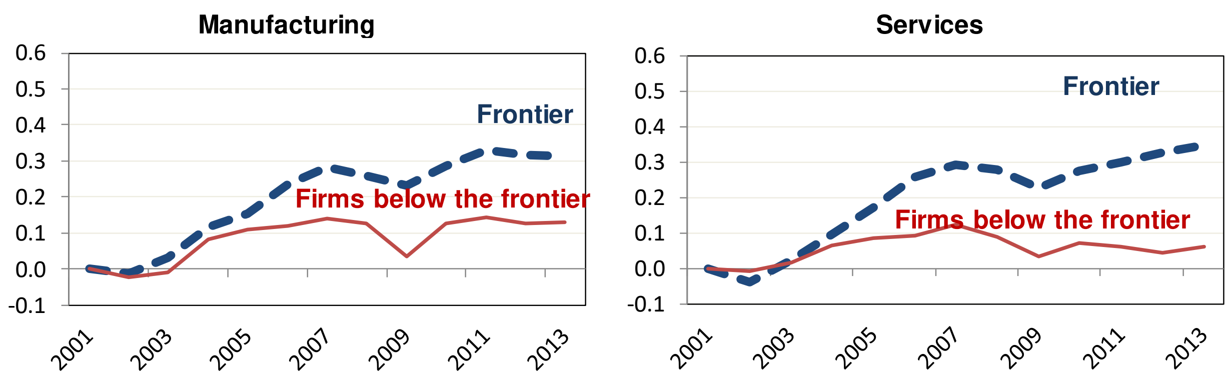
Figure A9

Labor productivity divergence within more narrowly defined industries

A: 3-digit industries



B: 4-digit industries

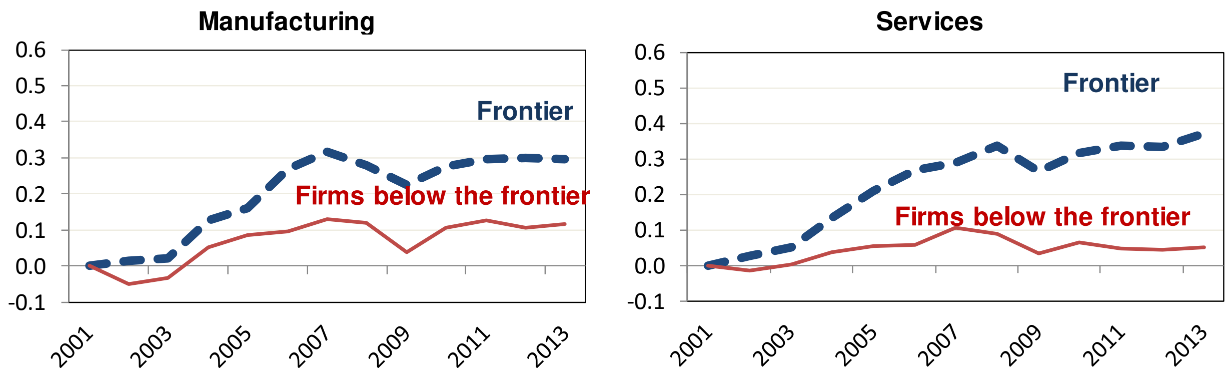


Notes: The global frontier is measured by the average of log labor productivity for the top 5% of companies with the highest productivity levels within each 3-digit (panel A) or 4-digit (panel B) industry. Laggards capture the average log productivity of all the other firms. Unweighted averages across 3 (or 4)-digit industries are shown for manufacturing and services, normalized to 0 in the starting year. The time period is 2001-2013. The vertical axes represent log-point differences from the starting year. Services refer to non-financial business services.

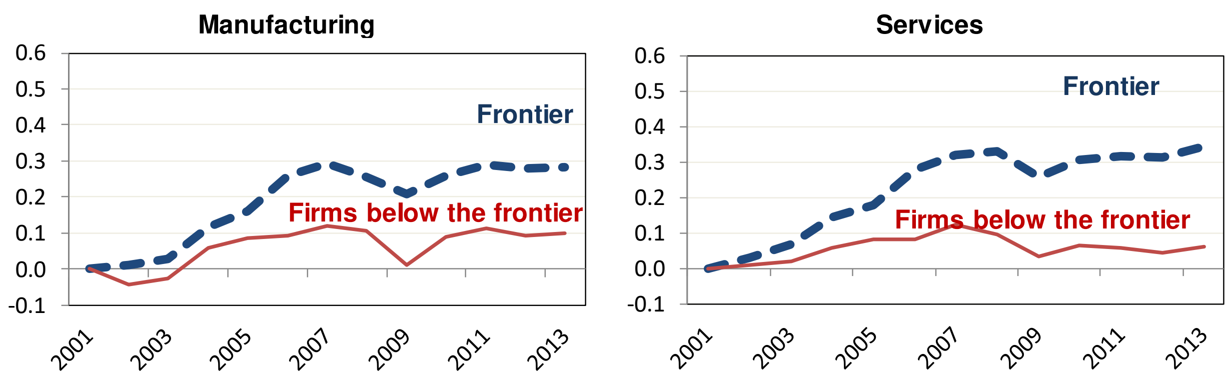
Figure A10

MFPR divergence within more narrowly defined industries

A: 3-digit industries



B: 4-digit industries

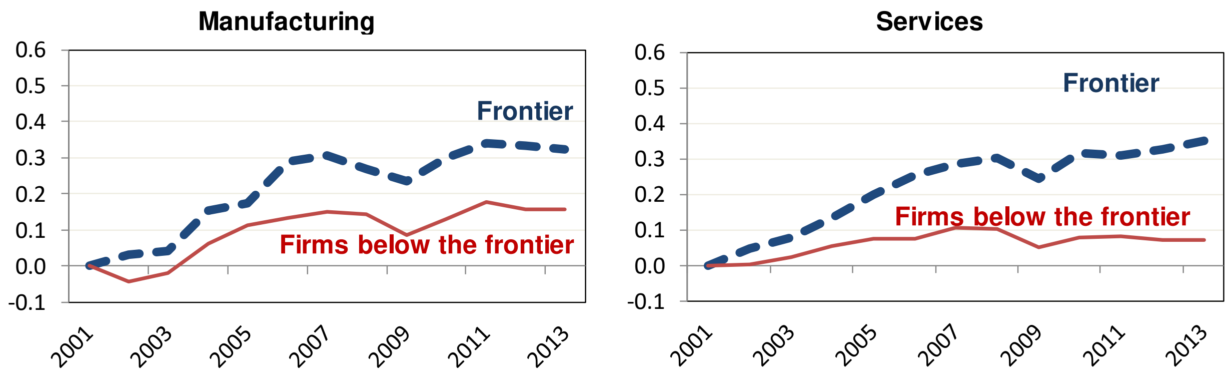


Notes: The global frontier group of firms is defined by the top 5% of companies with the highest MFPR levels within each 3-digit (panel A) or 4-digit (panel B) industry. Laggards capture the average log productivity of all the other firms. Unweighted averages across 3 (or 4)-digit industries are shown for manufacturing and services, normalized to 0 in the starting year. The time period is 2001-2013. MFPR uses the Wooldridge (2009) methodology based production function estimation conducted at the two-digit level to avoid having to work with too few observations per industry. The vertical axes represent log-point differences from the starting year. Services refer to non-financial business services.

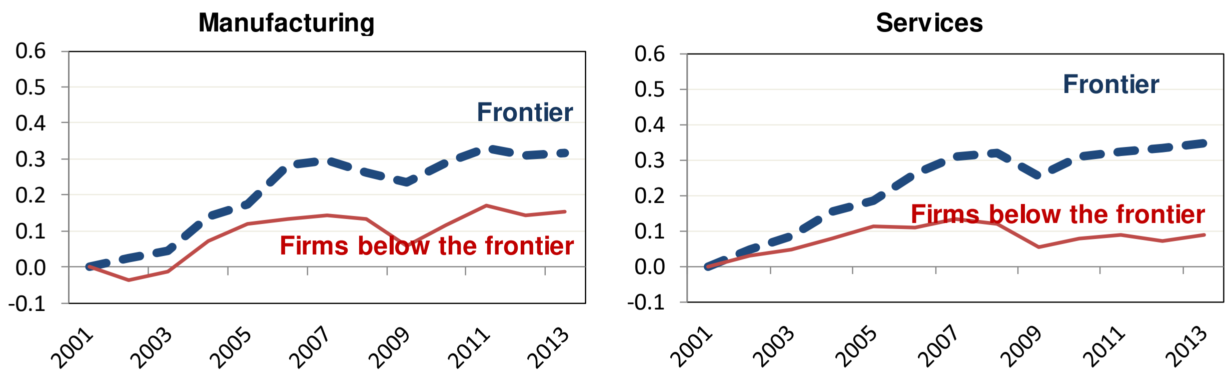
Figure A11

Markup corrected MFPR divergence within more narrowly defined industries

A: 3-digit industries



B: 4-digit industries



Notes: the global frontier is measured by the average of corrected MFPR for the top 5% of companies with the highest productivity levels within each 3-digit (panel A) or 4-digit (panel B) industry. Laggards capture the average markup corrected MFPR of all the other firms. Unweighted averages across 3 (or 4)-digit industries are shown for manufacturing and services, normalized to 0 in the starting year. MFPR uses the Wooldridge (2009) methodology based production function estimation, conducted at the two-digit level to avoid having to work with too few observations per industry, while the markup estimation used for corrected MFPR uses the De Loecker and Warzynski (2012) methodology. The time period is 2001-2013. The vertical axes represent log-point differences from the starting year. Services refer to non-financial business services.

Appendix B: Illustrative Simulations on Productivity Divergence

Two examples are used to generate time-series patterns of productivity frontier and laggards under different assumptions. In both of them, the evolution of the frontier is given by the following random-walk with drift process for firm-level MFP :

$$\begin{aligned} &\Delta MFP_{\mathrm{it}} = a + \varepsilon_{\mathrm{it}}, \quad \varepsilon_{\mathrm{it}} \sim N(0, \sigma_\varepsilon), \\ &MFP_{i0} \sim N(0, \sigma_{\mathrm{MF}P_0}) \end{aligned} \tag{B1}$$

where the following notations apply:

- *a:* Trend firm-level productivity growth: 0.5% per annum (i.e. 0.005 log point, mean value from the data)
- σ_ε: Standard deviation of firm-level annual productivity growth: 0.25 log-points (taken from data)
- $\sigma_{\mathrm{MF}P_0}$: Initial cross-sectional dispersion of MFP: 0.8 (st.dev. of log MFP from the data)

The frontier is obtained from a distribution as described above, by choosing its top 5% in each period.

B.1. Catching-up and market selection: strong convergence

In the case used to illustrate catching-up, the following law of motion is applied for firms outside the frontier group:

$$\Delta MFP_{\mathrm{it}} = \beta \left(\underbrace{MFP_{F,t-1} - MFP_{i,t-1}}_{\text{Gap from the frontier}} \right) + a + \varepsilon_{\mathrm{it}}, \quad \varepsilon_{\mathrm{it}} \sim N(0, \sigma_\varepsilon) \tag{B2}$$

where $MFP_{F,t-1}$ denotes the average of frontier firms in period -*t*-1, and β is the convergence parameter, set to 0.15 and is estimated from firm-level data (see Table C1, panel A, col. 1.). Note that this law of motion collapses to that of equation (B1) for firms at the frontier where the gap is zero.

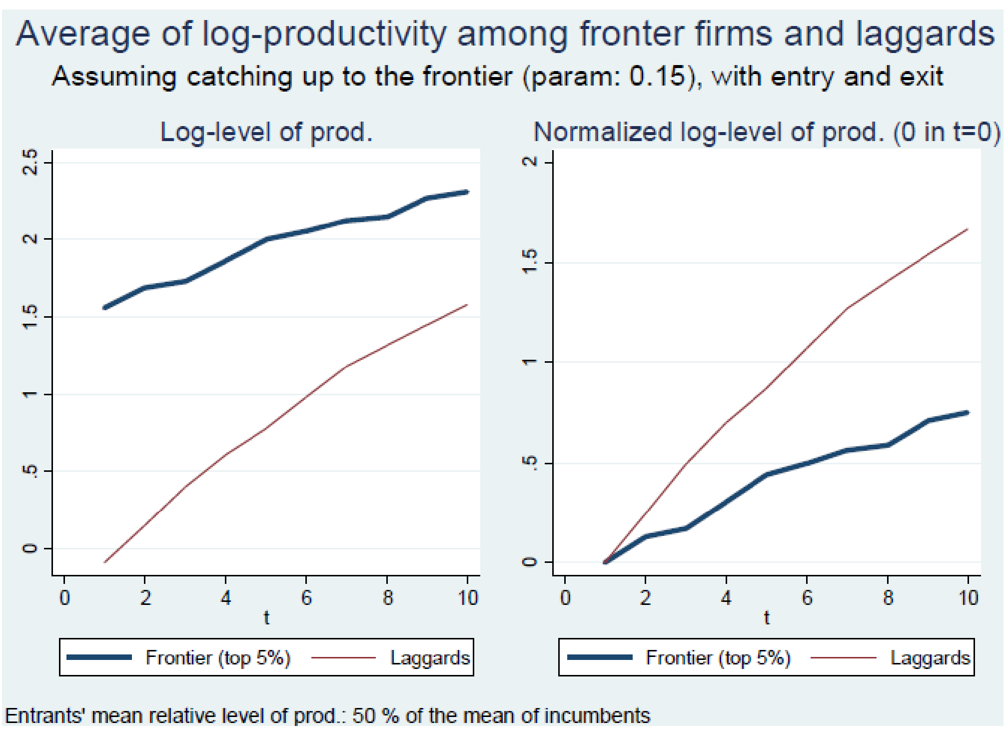
To capture market selection, a decreasing probability of exit is assumed as MFP is higher, reaching zero for the frontier and α for the firm with average productivity $E(MFP_{it})$.

$$P(\text{exit}_{\text{it}}) = \alpha \frac{MFP_{\text{Ft}} - MFP_{it}}{MFP_{\text{Ft}} - E(MFP_{it})},$$

where α is the average probability of exit, set to 0.06, also obtained from the data. Further, the number of entrants is such that it compensates for the number of exiting firms (to abstract away from changes in the size of the firm population, which is kept at 1,000). Their productivity level is centered at the mean of the MFP distribution of the incumbents and is normally distributed with the same standard deviation as above for the initial MFP level.

Figure B1

Simulation results: convergence



B.2. Weakening catch-up and weakening market selection: stalling convergence

To illustrate a case that produces increasing divergence, the following changes are introduced:

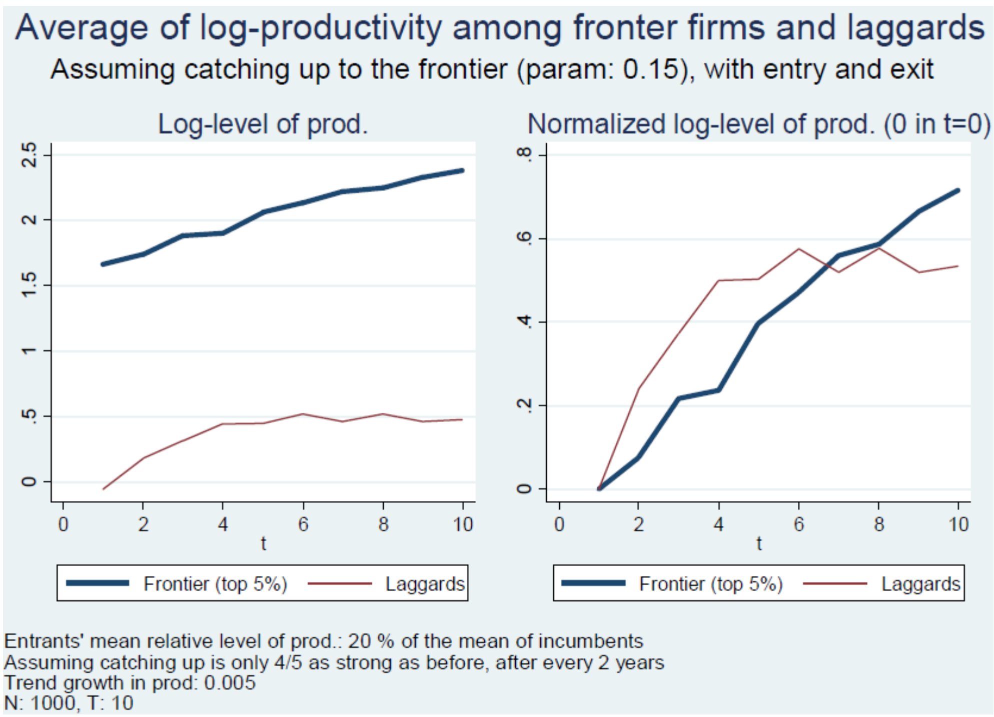
- *Laggard MFP growth:* β is declining by 20% after every 2 years
- *Exit*: uniform exit probability across the whole productivity distribution

$$P(\text{exit}_{\text{it}}) = 2\alpha$$

- *Entry*: the initial level is now centered to only 20% of the mean level of incumbents, and this level is halved after every 2 year period.

Figure B2

Simulation result: stalling convergence



These simulations illustrate that the strength of the catch-up process has to weaken over time, market selection has to be relatively weak and also worsening in order to produce a diverging pattern of the frontier away from the laggard firms.

Since a large or growing variance of shocks could have the potential to dominate the convergence force and could lead to a behavior or “random walk with a drift” (which would automatically imply growing dispersion in levels), we have also tested whether high (or growing) variance of shocks alone can account for the divergence. The answer is no, because it would require implausibly large variance of growth rates (about 0.5, in contrast with the observed 0.25), which in turn would lead to implausibly large growth at the frontier (instead of the observed growth of the frontier of about 0.3-0.4 over ten years, it would grow above 2).

Appendix C: Assessing the Role of Catching-up

This Appendix presents firm level evidence on the extent to which the pace of productivity convergence to the global productivity frontier has changed over time. See Section 3 in the main text for more details, including the exact specification.

The results suggest that on average across time, firms further behind the technological frontier have higher MFP growth, reflecting their ability to catch-up based on the adoption of a larger stock of unexploited technologies. However, there is also evidence that the pace of technological convergence via this mechanism has declined significantly over time. For example, while the base effect for the gap term – which provides the effect for 1998-2000 – is positive, the interactions with subsequent time periods are often negative. For example, Column 1 of Table A2 shows that the estimated coefficient on the lagged MFPR gap term declined by almost 30% from the late 1990s to the most recent period, with most of this decline realized by 2007. Moreover, this slowdown in the pace of productivity convergence is even more pronounced when the model is estimated using markup corrected MFPR (column 2).

These patterns are broadly robust to: *i*) different measures of MFP (Columns 3); *ii*) including firm age/size interactions with the frontier growth and gap terms to control for the potentially evolving composition of firms over time along these dimensions (Table C2); and *iii*) including industry*year fixed effects, which absorb the frontier growth and level terms, hence these results capture the declining strength of catching up (increasing persistence) in productivity, irrespective of the measurement of the frontier (Table C3).

Table C1

The pace of productivity convergence has slowed over time

Dependent variable: indicators of MFP growth at the firm level; 1998-2014

Baseline

Productivity measure	MFPR (Wooldridge)	Markup corrected MFP	MFPR (Solow residual)
Explanatory variables	(1)	(2)	(3)
$Gap_{j,t-1}$			
Base effect	0.147***	0.191***	0.111***
	(0.004)	*(0.009)*	*(0.009)*
2000-2002	0.006	-0.013	0.004
	(0.007)	*(0.013)*	*(0.011)*
2002-2005	-0.016***	-0.056***	-0.016
	(0.006)	*(0.010)*	*(0.010)*
2005-2007	-0.037***	-0.070***	-0.031***
	(0.006)	*(0.010)*	*(0.010)*
2007-2010	-0.023***	-0.076***	-0.029***
	(0.007)	*(0.011)*	*(0.010)*
2010-2014	-0.041***	-0.087***	-0.040***
	(0.005)	*(0.009)*	*(0.009)*
Δ MFP $Frontier_{j,t-1}$			
Base effect	0.203***	0.233***	0.193***
	(0.049)	*(0.059)*	*(0.045)*
2000-2002	-0.077	-0.146**	-0.077
	(0.057)	*(0.067)*	*(0.055)*
2002-2005	-0.050	-0.104	-0.065
	(0.058)	*(0.067)*	*(0.050)*
2005-2007	-0.059	-0.105	-0.139***
	(0.057)	*(0.065)*	*(0.051)*
2007-2010	0.073	-0.138*	0.025
	(0.067)	*(0.083)*	*(0.055)*
2010-2014	-0.095*	-0.188***	-0.122**
	(0.054)	*(0.064)*	*(0.049)*
R-squared	0.085	0.091	0.068
Country X year FEs	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes
Firm size and age cont	Yes	Yes	Yes
Obs. / countries	898737 / 21	516062 / 17	898120 / 21

Notes: Results are based on the regressions shown in equation (5) in Section 3. Cluster robust standard errors (at the industry-year level) in parentheses. Firm size and age captured by a rich 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 sample is restricted to firms that have at least 20 employees on average over time. Notation for p-values: *** p<0.01, ** p<0.05, * p<0.1

Table C2

The pace of productivity convergence has slowed over time

Dependent variable: indicators of MFP growth at the firm level; 1998-2014

Age/Size Interactions

Productivity measure		MFP (Wooldridge)	Markup corrected MFP	MFP (Solow residual)
Explanatory variables		(1)	(2)	(3)
$Gap_{j,t-1}$				
	Base effect	0.216***	0.240***	0.176***
		(0.007)	*(0.013)*	*(0.010)*
	2000-2002	0.006	-0.012	0.004
		(0.007)	*(0.013)*	*(0.011)*
	2002-2005	-0.016***	-0.052***	-0.016*
		(0.006)	*(0.010)*	*(0.010)*
	2005-2007	-0.036***	-0.061***	-0.029***
		(0.006)	*(0.010)*	*(0.010)*
	2007-2010	-0.021***	-0.070***	-0.027***
		(0.007)	*(0.011)*	*(0.010)*
	2010-2014	-0.038***	-0.081***	-0.037***
		(0.005)	*(0.009)*	*(0.009)*
Δ MFP $Frontier_{j,t-1}$				
	Base effect	0.184***	0.245***	0.151***
		(0.057)	*(0.080)*	*(0.052)*
	2000-2002	-0.076	-0.135**	-0.076
		(0.056)	*(0.067)*	*(0.055)*
	2002-2005	-0.048	-0.090	-0.071
		(0.058)	*(0.067)*	*(0.051)*
	2005-2007	-0.055	-0.087	-0.142***
		(0.056)	*(0.065)*	*(0.051)*
	2007-2010	0.074	-0.124	0.022
		(0.066)	*(0.081)*	*(0.056)*
	2010-2014	-0.095*	-0.176***	-0.126**
		(0.053)	*(0.064)*	*(0.049)*
R-squared		0.087	0.094	0.070
Country X year FEs		Yes	Yes	Yes
Industry FEs		Yes	Yes	Yes
Firm size and age controls		Yes	Yes	Yes
$Gap_{j,t-1}$ X Sizeclass FEs, Frontier $growth_{j,t-1}$ X Sizeclass FEs		Yes	Yes	Yes
$Gap_{j,t-1}$ X Ageclass FEs, Frontier $growth_{j,t-1}$ X Ageclass FEs		Yes	Yes	Yes
Obs. / countries		898737 / 21	516062 / 17	898120 / 21

Notes: Results are based on the regressions shown in equation (5) in Section 3. Cluster robust standard errors (at the industry-year level) in parentheses. Firm size and age captured by a rich 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 sample is restricted to firms that have at least 20 employees on average over time. Notation for p-values: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table C3 The pace of productivity convergence has slowed over time

Dependent variable: indicators of MFP growth at the firm level; 1998-2014

Including Industry × Year Fixed Effects

Productivity measure		MFPR (Wooldridge)	Markup corrected MFP	MFPR (Solow residual)
Explanatory variables		(1)	(2)	(3)
$Gap_{j,t-1}$				
	Base effect	0.158***	0.196***	0.115***
		(0.005)	*(0.010)*	*(0.012)*
	2000-2002	0.008	-0.012	-0.002
		(0.008)	*(0.014)*	*(0.019)*
	2002-2005	-0.025***	-0.063***	-0.018
		(0.007)	*(0.011)*	*(0.014)*
	2005-2007	-0.044***	-0.076***	-0.028*
		(0.007)	*(0.012)*	*(0.015)*
	2007-2010	-0.030***	-0.079***	-0.029**
		(0.007)	*(0.011)*	*(0.014)*
	2010-2014	-0.053***	-0.093***	-0.050***
		(0.006)	*(0.010)*	*(0.012)*
R-squared		0.096	0.099	0.077
Country X year FEs		Yes	Yes	Yes
Industry FEs		Yes	Yes	Yes
Firm size and age controls		Yes	Yes	Yes
Obs. / countries		898737 / 21	516062 / 17	898120 / 21

Notes: Results are based on the regressions shown in equation (5) in Section 3. Cluster robust standard errors (at the industry-year level) in parentheses. Firm size and age captured by a rich 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 sample is restricted to firms that have at least 20 employees on average over time. Notation for p-values: *** p<0.01, ** p<0.05, * p<0.1

Table C4 The frontier group of firms is becoming more entrenched

Proportion of frontier firms (in %) in year t *according to their position in the distribution in* t-1

A: MFPR

Sector	Time periods	Position in the distribution in t-1 in top 5%	in top 10%	in top 20%
Manufacturing	2001-2003	53.4	67.6	74.0
	2011-2013	59.2	72.5	78.7
Services	2001-2003	48.3	62.0	68.8
	2011-2013	55.2	71.1	77.4

A: Markup corrected MFPR

Sector	Time periods	Position in the distribution in t-1 in top 5%	in top 10%	in top 20%
Manufacturing	2001-2003	46.9	60.4	69.4
	2011-2013	52.9	69.6	77.7
Services	2001-2003	42.2	58.2	69.7
	2011-2013	48.4	68.3	82.6

Notes: The tables show the proportion of firms classified as global frontier firms at time *t* – i.e. in the top 5% of the MFPR or markup corrected MFPR distribution – according to their status one year earlier (*t*-1). Estimates are averaged over two periods towards the beginning and end of our sample. For example, the bottom part of Panel A shows that on average over the period 2011-2013 in services, 55.2% of frontier firms (i.e. top 5%) were present in the frontier grouping one year earlier, while 71.1% had MFPR levels in the top 10% and 77.4% had MFPR levels in the top 20%.

Appendix D: Aggregate Implications

In this Appendix we show robustness tests on the results that industries that are characterized by a greater productivity gap increase between laggards and frontier are also those that experience weaker aggregate productivity growth. The results are robust to changing the long-difference period (4 and 6 years, see Table D1), to using an alternative definition for the frontier (time-varying 5% instead of a fixed number, see Table D2) and in most cases also when we use firm-level labor productivity instead of MFP (based on the Wooldridge, 2009, method; see Table D3).

The sample covers 23 countries over 2001-2013 for 54 detailed industries in the non-financial market sector (ISIC Rev 4 industry codes 10 to 82). This excludes small industries that have less than 50 firms on average across years: mining (5-9), Tobacco (12), Air Transport (51), Veterinary activities (75), Services to buildings and landscape activities (81). We also exclude employment agencies (78) due to labor input measurement difficulties.

Table D1

Productivity divergence and aggregate productivity growth: a negative relationship

Aggregate productivity regressed on the productivity gap (long-differences over 4 or 6 years)

Long-difference window	Four years				Six years			
Dependent variable: aggregate productivity measure	Δ MFP		Δ Labour productivity		Δ MFP		Δ Labour productivity	
Productivity gap measure variant:	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Productivity gap	-0.248***	-0.262***	-0.265***	-0.271***	-0.238***	-0.273***	-0.218**	-0.253***
	(0.082)	(0.065)	(0.087)	(0.075)	(0.086)	(0.068)	(0.088)	(0.070)
R-squared	0.606	0.622	0.478	0.489	0.739	0.751	0.663	0.673
Industry and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	486	486	486	486	378	378	378	378

Notes: All variables are measured in log differences over four or six year periods (with overlaps). Standard errors are clustered at the industry level. The productivity gap is defined by using firm-level MFP (Wooldridge, 2009, methodology). The sample covers 54 industries and 23 countries over 2001-2013. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table D2 Productivity divergence and aggregate productivity growth: a negative relationship

Aggregate productivity regressed on the productivity gap, using an alternative definition for the frontier

(long-differences over 5 years)

Dependent variable: aggregate productivity measure	Δ MFP		Δ Labour productivity	
Productivity gap measure variant:	Mean	Median	Mean	Median
Explanatory variable	(1)	(2)	(3)	(4)
Δ Productivity gap	-0.191*	-0.229***	-0.201*	-0.248***
	(0.099)	*(0.082)*	*(0.106)*	*(0.088)*
R-squared	0.667	0.680	0.551	0.564
Industry and year fixed effects	Yes	Yes	Yes	Yes
Observations	432	432	432	432

Notes: All variables are measured in log differences over five year periods (with overlaps). Standard errors are clustered at the industry level. The productivity gap is defined by using firm-level MFP (Wooldridge, 2009, methodology). The sample covers 54 industries and 23 countries over 2001-2013. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table D3 Productivity divergence and aggregate productivity growth: a negative relationship

Aggregate productivity regressed on the labor productivity gap (long-differences over 4, 5 or 6 years)

Long-difference window	Four years		Five years		Six years	
Dependent variable: aggregate productivity measure	Δ Labour productivity		Δ Labour productivity		Δ Labour productivity	
Productivity gap measure variant:	Mean	Median	Mean	Median	Mean	Median
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
Δ Productivity gap	-0.122	-0.126*	-0.124	-0.163**	-0.167**	-0.194***
	(0.082)	*(0.074)*	*(0.086)*	*(0.077)*	(0.076)	(0.062)
R-squared	0.455	0.459	0.547	0.558	0.660	0.669
Industry and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	540	540	432	432	378	378

Notes: All variables are measured in log differences over four, five or six year periods (with overlaps). Standard errors are clustered at the industry level. The productivity gap is defined by using firm-level value added based labor productivity. The sample covers 54 industries and 23 countries over 2001-2013. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table D4 Productivity divergence and aggregate productivity growth: a negative relationship

Aggregate productivity regressed on the MFP gap, controlling for the relative size of the frontier (long-differences over 5 years)

Dependent variable: aggregate productivity measure	Δ MFP		Δ Labour productivity	
Productivity gap measure variant:	Mean	Median	Mean	Median
Explanatory variables	(1)	(2)	(3)	(4)
Δ Productivity gap	-0.225**	-0.280***	-0.209**	-0.258***
	(0.093)	*(0.069)*	*(0.100)*	*(0.084)*
Δ Relative size	0.027	0.033	0.015	0.021
	(0.022)	*(0.022)*	*(0.029)*	*(0.028)*
R-squared	0.686	0.708	0.559	0.575
Industry and year fixed effects	Yes	Yes	Yes	Yes
Observations	432	432	432	432

Notes: All variables are measured in log differences over five year periods (with overlaps). Standard errors are clustered at the industry level. The productivity gap is defined by using firm-level MFPR (Wooldridge, 2009). The relative size of the frontier is measured as the log of the ratio of mean employment between the frontier and laggard groups, within each detailed industry and year. The sample covers 54 industries and 23 countries over 2001-2013. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Appendix E: The Evolution of Product Market Regulation

The indicators reveal that there is considerable scope for further product market reform in many OECD countries, particularly in market services where the increase in MFP divergence has been most striking (Gal and Hijzen, 2016 and Figure E1). Within non-manufacturing industries, most reform activity over the past 15 years has been concentrated in network industries (i.e. energy, transport and communication), and this is reflected in both a decline in the median level and dispersion of market regulation across countries. While there remains some scope for further reform action in specific network industries (particularly road and rail transportation) and countries, the need for reforms in retail trade and in particular professional services is clear. Between 1998 and 2013, the median restrictiveness of product market regulations was little changed in professional services (Panel B of Figure E1), while the dispersion in the restrictiveness of market regulations across countries in these sectors remains high.

Table E1

Descriptive statistics: PMR and national MFP gaps

Unit of observation: country-industry-year

	PMR	Gap in MFP	Gap in markup corr. MFP
Mean	0.607	1.294	1.272
Median	0.811	1.163	1.127
St.dev.	0.673	0.470	0.523
N	564	564	471

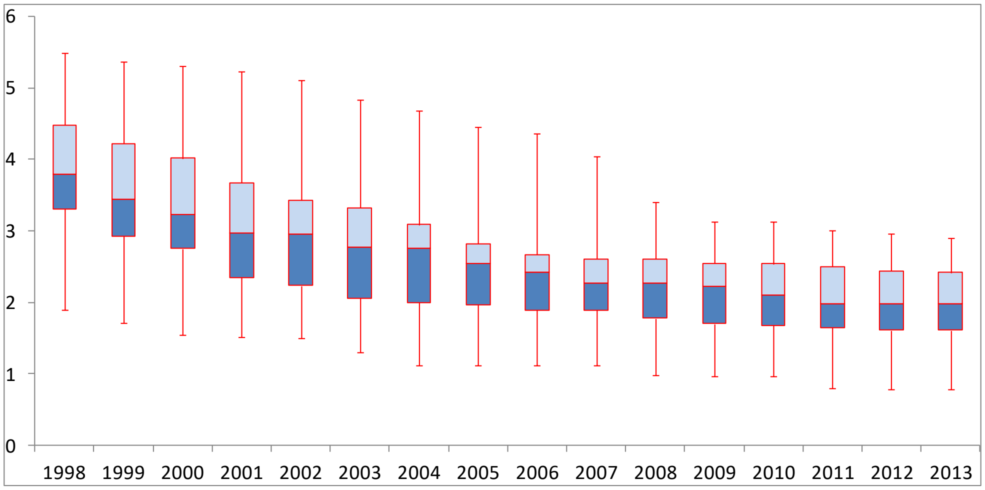
Notes: All variables are measured in logs. Regulated services include those industries that are covered by the PMR indicator (see details in Appendix D).

Sources: Orbis (for productivity gaps); OECD Product Market Regulation Database (for the PMR indicator).

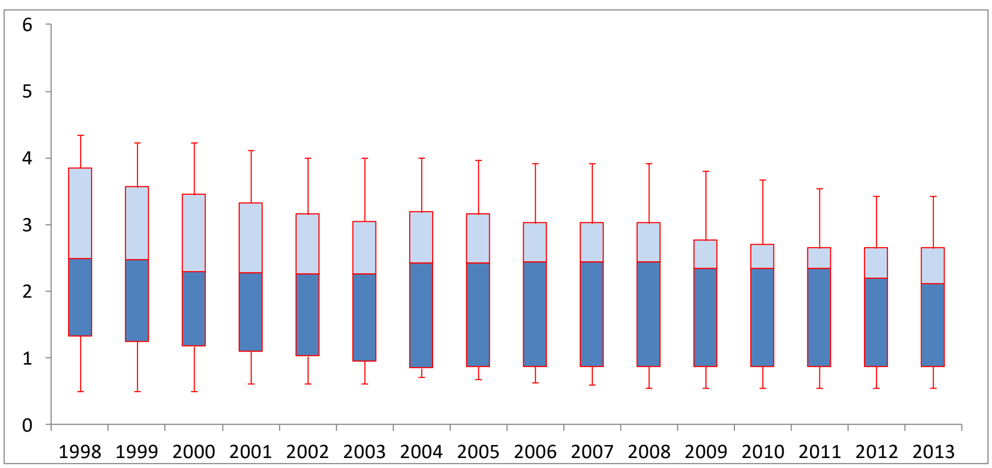
Figure E1

The restrictiveness of product market regulations over time, 1998-2013

A: Network industries



B: Professional services



Notes: The PMR indicator varies between 0 and 6, and higher values indicate more stringent and less competition-friendly regulation. The horizontal line in the boxes represents the median, the upper and lower edges of each boxes reflect the 25th and 75th percentiles and the markers on the extremes denote the maximum and the minimum across OECD countries.

Source: calculations by Gal and Hijzen (2016) based on OECD indicators on product market regulation (PMR) and additional information on the timing of reforms for retail and professional.

E.1. Robustness on MFP divergence and PMR

This section presents a series of robustness checks on the impact of product market regulation on the productivity gap between the global frontier and other firms.

Table E2

Robustness to changing the long difference window

Estimation method – four-year long differences

Dependent variable	Δ MFP gap		Δ Mark-up corrected MFP gap	
Explanatory variable	(1)	(2)	(3)	(4)
Δ Product Market Regulation$_{s,c,t}$	0.166***	0.190***	0.277**	0.292**
	(0.057)	(0.064)	(0.112)	(0.142)
Country fixed effects	YES	NO	YES	NO
Industry fixed effects	YES	YES	YES	YES
Year fixed effects	YES	NO	YES	NO
Country X year fixed effects	NO	YES	NO	YES
Observations	512	512	421	421
R-squared	0.158	0.287	0.228	0.397

B: Estimation method – six-year long differences

Dependent variable	Δ MFP gap		Δ Mark-up corrected MFP gap	
Explanatory variable	(1)	(2)	(3)	(4)
Δ Product Market Regulation$_{s,c,t}$	0.267***	0.277***	0.452***	0.452***
	(0.070)	(0.096)	(0.128)	(0.149)
Country fixed effects	YES	NO	YES	NO
Industry fixed effects	YES	YES	YES	YES
Year fixed effects	YES	NO	YES	NO
Country X year fixed effects	NO	YES	NO	YES
Observations	400	400	329	329
R-squared	0.297	0.413	0.413	0.550

Notes: Cluster robust standard errors (at the country-industry level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Both the MFP gap and the PMR indicator are measured in log terms. The MFP gap is calculated at the country-industry-year level, by taking the difference between the average log productivity at the frontier and among other firms. The time period is 1998-2013. See more details in the Section 5.4.

Table E3

Robustness to median MFP of laggard firms

Estimation method – five-year long differences

Dependent variable	Δ MFP gap		Δ Mark-up corrected MFP gap	
Explanatory variable	(1)	(2)	(3)	(4)
Δ Product Market Regulation$_{s,c,t}$	0.190**	0.234**	0.275***	0.262**
	(0.076)	(0.089)	(0.093)	(0.114)
Country fixed effects	YES	NO	YES	NO
Industry fixed effects	YES	YES	YES	YES
Year fixed effects	YES	NO	YES	NO
Country X year fixed effects	NO	YES	NO	YES
Observations	458	458	376	376
R-squared	0.199	0.316	0.330	0.459

Notes: Cluster robust standard errors (at the country-industry level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Both the MFP gap and the PMR indicator are measured in log terms. The MFP gap is calculated at the country-industry-year level, by taking the difference between the global frontier and the median of log productivity of non-frontier firms. The time period is 1998-2013.

Appendix F: Data and Productivity Measurement

Table F1

Information providers underlying the Orbis Database

Information provider	Country
Bisnode	Czech Republic, Slovakia
Bureau van Dijk	Luxembourg
Cerved	Italy
Cortera	US
Coface Slovenia	Slovenia
Creditreform Austria	Austria
Creditreform Latvia	Latvia
Creditreform Luxembourg	Luxembourg
Creditreform-Interinfo	Hungary
Ellisphere	France
Experian	NorwayDenmark
ICAP	Greece
InfoCredit	Poland
Informa	Spain
Informa Portugal	Portugal
Jordans	United Kingdom, Ireland
Kamer van Koophandel	Netherlands
Krediidiinfo	Estonia
LexisNexis	Netherlands
National Bank of Belgium	Belgium
NICE Info	Korea
Suomen Asiakastieto	Finland
Thomson Reuters	US - Listed companies
TSR	Japan
UC	Sweden
Verband der Vereine Creditreform	Germany

Source: Bureau van Dijk, reflecting their set of information providers as of March 2016.

F.1. Data

This paper uses a harmonized firm-level productivity database, based on underlying data from the recently updated OECD-Orbis database (see Gal, 2013). The database contains several productivity measures (variants of labor productivity and multi-factor productivity, MFP) and covers up to 24 OECD countries over the period 1997 to 2014 for the non-farm, non-financial business sector.[41] These countries are: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Great Britain, Greece, Hungary, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Portugal, Spain, Sweden, Slovenia, the Slovak Republic and the United States. The country coverage is somewhat smaller in the policy analysis, given the limited availability of the policy indicators, or lack thereof, for some of the 24 countries considered. The industry coverage means retaining industries with 2 digit codes from 5 to 82, excluding 64-66 in the European classification system NACE Rev 2, which is equivalent to the international classification system ISIC Rev. 4 at the two-digit level.

As discussed in Gal (2013), these data come from annual balance sheets and income statements, collected by an electronic publishing firm called Bureau van Dijk, using a variety of underlying sources ranging from credit rating agencies (e.g. Cerved in Italy) to national banks (e.g. National Bank of Belgium for Belgium) as well as financial information providers (e.g. Thomson Reuters for the US). See the full list of information providers to Bureau van Dijk regarding financial information for the set of countries retained in the analysis in Table F1.

Orbis is the largest cross-country company-level database that is available and accessible for economic and financial research. However, since the information is primarily collected for use in the private sector typically with the aim of financial benchmarking, a number of steps need to be undertaken before the data can be used for economic analysis. The steps we apply closely follow suggestions by Kalemli-Ozcan, Sorensen, Villegas-Sanchez, Volosovych and Yesiltas (2015) and previous OECD experience (Gal, 2013). Three broad steps are (i) ensuring comparability of monetary variables across countries and over time (PPP conversion and deflation); (ii) deriving new variables that will be used in the analysis (capital stock, productivity); and (iii) keeping company accounts with valid and relevant information for our present purposes (filtering or cleaning). Finally, Orbis is a subsample of the universe of companies for most countries, retaining the larger and hence probably more productive firms. To mitigate problems arising from this, we exclude firms with less than 20 employees on average over their observed lifespan.

[41] This means retaining industries with 2 digit codes from 5 to 82, excluding 64-66 in the European classification system NACE Rev 2, which is equivalent to the international classification system ISIC Rev. 4 at the two-digit level.

A number of issues that commonly affect productivity measurement should be kept in mind when using this data. First, differences in the quality and utilisation of capital and labor inputs cannot be accounted for as the capital stock is measured in book values and labor input by the number of employees.[42] Secondly, to measure output in internationally comparable price, we use the country-industry level purchasing power parity database of Inklaar and Timmer (2014). However, there remain important challenge, details therein for the tradeoffs involved in deriving their PPP measures. Finally, similar to most firm-level datasets, Orbis contains variables on outputs and inputs in nominal values and no additional separate information on firm-specific prices and quantities (i.e. we observe total sales of steel bars, but no information on tonnes of steel bars sold and price per ton), thus output is proxied by total revenues or total value added. Even though we deflate these output measures by country-industry-year level deflators (at the two-digit detail), differences in measured (revenue) productivity across firms within a given industry may still reflect both differences in technology as well as differences in market power.[43] As described further below, we attempt to correct our productivity measures for differences in market power by deriving firm- and time- specific markups following De Loecker and Warzynski (2012).

F.2. Variable definitions

Value added

It is defined as the sum of gross profits and the costs of employees. More specifically, value added is the sum of the following accounting categories as available from earnings statements: *Profit (net income) for the period + Depreciation + Taxation + Interests paid + Cost of employees.*

Capital stock

[42] The measurement of intangible fixed assets in the balance sheets follows accounting rules, hence the total fixed assets (sum of tangibles and intangibles) may understate the overall capital stock (Corrado et al, 2009). Moreover, different depreciation rates and investment price deflators cannot be applied, since an asset type breakdown is not available.

[43] In the above example, it is unclear whether revenue based productivity is higher because the firm is producing more steel bars, or whether the firm's higher observed productivity is driven by higher prices reflecting high markups, which the firm can charge because of a lack of competition, for example.

It is derived from the book value of fixed assets using the perpetual inventory method on gross investments - deflated by two-digit country-specific investment deflators – and the initially observed fixed assets. Firm-specific depreciation rates are derived using the book value of depreciation and fixed assets. To obtain a measure of real capital stock K_{it}, the perpetual inventory method (PIM) is applied by using the book value of fixed assets $K_{\text{it}}^{\text{BV}}$ (for each firm *i* and year *t*), derived gross investment series from them and two-digit industry deflators. More precisely, the dynamic evolution of the real capital stock K_{it} is given by the degree of depreciation δ_{it}, investments I_{it} and the value of the capital stock in the previous period $K_{i,t-1}$ in the following manner:

$$K_{\text{it}} = K_{i,t-1}(1 - \delta_{\text{it}}) + I_{\text{it}}.$$

The depreciation rate is defined as the observed book value of depreciation divided by the sum of the previous value of capital stock and depreciation: $\delta_{\text{it}} = \frac{\text{Depr}_{\text{it}}^{\text{BV}}}{\text{Depr}_{\text{it}}^{\text{BV}} + K_{i,t-1}^{\text{BV}}}$. Using firm-specific book value depreciation rates has its limitation but we view it better than the alternative of using industry-specific depreciation rates based on more accurate measures for changes in asset values over time but which are by nature homogeneous across firms. In contrast firm-specific depreciation rates – even if book values -– will reflect differences in the asset composition (i.e. firms that use more structures and buildings but fewer machinery and equipment will have lower depreciation rates). Since the balance sheet data is harmonized across countries by the data provider of Orbis, the role of country specific differences in accounting rules for depreciation rates should be minimized. In any case in the regressions containing country*time fixed effects, this issue is further mitigated.

We defined the real value of gross investment I_{it} as the annual change in book value of fixed tangible assets $K_{\text{it}}^{\text{BV}}$ plus depreciation $\text{Depr}_{\text{it}}^{\text{BV}}$, deflated by the gross fixed capital formation deflator PI_{cjt} (specific to each country *c* and two-digit industry *j*, sourced from detailed OECD National Accounts):

$$I_{\text{it}} = (K_{\text{it}}^{\text{BV}} - K_{i,t-1}^{\text{BV}} + \text{Depr}_{\text{it}}^{\text{BV}})/PI_{\text{cjt}}.$$

Finally, the starting value of the real capital stock K_{i0} for each f irm is the book value of fixed assets deflated by the investment deflator:

$$K_{i0} = K_{i0}^{\mathrm{BV}} / PI_{cj0}.$$

Missing values in the raw data for fixed assets are filled up by linear interpolation, invoking the implicit assumption that depreciation offsets gross investments ("steady state"). The same principle is applied for missing values for depreciation.

MFP

Our preferred measure of MFP is based on a production function estimation, using the Wooldridge (2009) control function based methodology, with the number of employees and real capital as inputs and materials as the proxy variable. More specifically, we assume a value added based Cobb-Douglas production function and estimate regressions of the following form, separately for each detailed (NACE Rev 2, 2-digit level) industry j:

$$y_{it} = \beta_K^j k_{it} + \beta_L^j l_{it} + \nu_c^j + \eta_t^j + \varepsilon_{\mathrm{it}}, \qquad \text{for all industries } j = 1, \dots J \tag{F1}$$

where y_{it} denotes log of real value added, k_{it} denotes the log of real capital stock, and l_{it} the log of the number of employees. ν_c^j and η_t^j are country and year fixed effects, respectively (allowed to vary for each 2-digit industry), and $\varepsilon_{\mathrm{it}}$ is the error term. Real values for value added are obtained by dividing nominal values by country specific two-digit industry deflators.

We employ the one-step GMM estimation method proposed by Wooldridge (2009), which mitigates the endogeneity problem of input choices by using material inputs as proxy variables for productivity and lagged values of labor as instruments. This approach addresses the critique of Ackerberg et al (2015) on the identification of the labor coefficient, and also makes estimations more efficient and robust since it avoids using a two-step approach.

More specifically, in order to avoid the endogeneity of inputs and a correlation between the error term and the choice of labor input (violating $E(\varepsilon_{\mathrm{it}} | l_{\mathrm{it}}) = 0$), the estimation is done through one-step GMM with the following form:

$$y_{\mathrm{it}} = \beta_K^j k_{\mathrm{it}} + \beta_L^j l_{\mathrm{it}} + g(k_{it-1}, m_{it-1}) + \nu_{c,j} + \eta_{t,j} + u_{it}. \tag{F2}$$

The function $g(.)$ is a 3rd degree polynomial including all base terms, 2nd and 3rd order interactions of k_{it-1} and m_{it-1}. The lagged value of labor l_{it-1} is used as an instrument along with all terms containing $k_{\mathrm{it}}, k_{it-1}$ and m_{it-1}, which act as their own instruments as they are assumed to be predetermined. Standard errors are clustered at the firm level.

Finally, *MFPR, i.e.* revenue based multi-factor productivity[44] is defined in logs using the estimated coefficients (output elasticities) for capital and labor in equation (F2):[45]

$$MFPR_{\mathrm{it}} \doteq y_{\mathrm{it}} - \hat{\beta}_K^j k_{\mathrm{it}} - \hat{\beta}_L^j l_{\mathrm{it}}. \tag{F3}$$

The production function is estimated separately for each two-digit industry but pooled across all countries, controlling for country and year fixed effects. This allows for inherent technological differences across industries, while at the same time ensures comparability of MFP levels across countries and over time by having a uniform labor and capital coefficient along these dimensions.

Before running the production function estimations, a number of additional cleaning rules were applied. In particular, within each two-digit industry, those observations are excluded where log(value added/employment), log(capital/employment) and log (materials/employment) are outside the top or bottom 0.5% of their distribution to avoid the impact of extreme observations on the production function estimation.

The estimated coefficients are statistically significant and economically meaningful in that the labor coefficients tend to be higher in services than in manufacturing and overall they range

[44] The use of industry level deflators, rather than firm level prices leads to a wedge between firm and industry level prices and thus our productivity measure will also be affected by the profitability of firms, driven by their market power. In order to correct for the potential impact of market power on our productivity estimates we also estimate firm- and time specific markups and correct our MFP measure for them.

[45] To avoid limiting the sample size unnecessarily, the MFP measures are also calculated for those firms where intermediate inputs are not observed. With the actual implementation of Wooldridge (2009), we follow the Stata program codes provided by Petrin and Levinsohn (2012).

between 0.6 and 0.85. The production function estimation results are available upon request. In order to maximize coverage for our MFP measures, they are also calculated as a residual from the estimated production function for those firms where materials (our measure of intermediate inputs) are not available. However, the first step of the markup estimation also relies on materials, hence the sample size reduction in the markup corrected MFP measures.

Markups

In order to mitigate the limitations of firm-level productivity measurement due to not observing firm-level prices, we correct our revenue based MFP measure by firm- and time-varying markups applying the markup estimation methodology of De Loecker and Warzynski (2012). We introduce a notation for markup corrected MFP estimates as MFPR^{c}, and we define it for each firm i and year t as follows:

$$MFPR_{it}^{c} = MFPR_{it} - \log(\mu_{it}), \tag{F4}$$

influenced by market power changes under the assumption that at least one input of production is fully flexible (e.g. labor or materials).

The markup is derived from the supply-side approach originally proposed by Hall (1986) and more recently re-explored and adapted to firm-level applications by De Loecker and Warzynski (2012). As described therein, the approach computes markups without any assumptions about the demand function, but only relying on available information on output and inputs. Their two crucial assumptions are that at least one input is fully flexible and that firms minimize costs. Thus, the markup – defined as the ratio of the output price P over marginal cost MC – is derived from the first order condition of the plant's cost minimization problem with respect to the flexible input k as:

$$\mu_{it}^{(k)} = \frac{P_{it}}{MC_{it}} = \frac{\text{Output Elasticity}_{ikt}}{\text{Output Share}_{ikt}} \tag{F5}$$

$$\mu_{it}^{(k)} = \frac{\hat{\beta}_{k}^{j}}{\tilde{ws}_{it}}. \tag{F6}$$

For example, in case the flexible input is taken to be labor ($m = L$), its coefficient $\hat{\beta}_L^j$ in the numerator of equation (F6) is estimated using the GMM estimation method by Wooldridge (2009), as described above. The denominator is obtained by using a prediction of firm-level value added by a rich polynomial function of observable inputs in order to retain only the anticipated part of output developments.[46] The rationale for using this correction is the assumption that firms do not observe unanticipated shocks to production when making optimal input decisions.

Given that labor input may not be fully flexible – especially in countries with rigid labor markets – we also calculated markups using materials as the fully flexible input for a subset of 18 countries for which data are available. In that case, a gross-output based production function is estimated to obtain a coefficient for materials, again following Wooldridge (2009). As shown in Appendix A, the divergence in MFP is robust to these different choices.

As noted in De Loecker and Warzynski (2012), the low demand in terms of additional assumptions of their approach and the lack of information on firm level prices bear some costs. Given that we do not observe firms' physical output, the approach is only informative on the way markups change over time (not their level) and in relative terms, i.e. on the correlation with firm characteristics (e.g. productivity, size, export status) rather than in absolute levels. In what follows therefore, we will focus at relative trends in markups for frontier and laggard firms.

We provide below a more detailed description of the time varying firm-specific markup calculation as proposed by De Loecker and Warzynski (2012). Under cost minimization and flexibility of at least one of the inputs X it can be shown that the output elasticity equals (left hand side below) its cost share (right hand side):

$$\frac{\partial Y_{it}}{\partial X_{it}} / \frac{Y_{it}}{X_{it}} = \frac{P_X X_{it}}{MC_{it} Y_{it}} \tag{F7}$$

where Y, C and P^X are output, marginal cost and input price, respectively.

Then by introducing a definition for the markup as

[46] The polynomial includes all possible interactions between labor, capital and materials containing first and second degree terms, along with first and second degree base effects. This adopts the Stata program code provided by De Loecker and Warzynski (2012) with their online Appendix, with the difference that for computational reasons we omitted the third degree terms.

$$\mu_{it} = \frac{P_{it}}{MC_{it}},$$

we can rewrite equation (F7) as follows:

$$\mu_{it} = \frac{\frac{\partial Y_{it}}{\partial X_{it}}}{\frac{Y_{it}}{X_{it}}} / \frac{P_X X_{it}}{P_{it} Y_{it}} = \ Output\ Elasticity_{it}^{X} / Output\ Share_{it}^{X}.$$

This is the relationship that the actual implementation will exploit. The exact steps of that are as follows:

1. Identifying the output elasticities of inputs from estimating the production function using Wooldridge (2009), obtaining $\hat{\beta}_L^j$, since labor is assumed to be the flexible input in our baseline case. As a robustness check we also calculate – and show our main result of productivity divergence in Figure A8 in Appendix A – a gross output based production function where materials enter as a separate input and they are considered as the flexible input for the markup calculation.
2. Calculating the share of input costs in revenue, using as the baseline employment as flexible input. This boils down to a variant of the wage share $\tilde{ws}_{\mathrm{it}} = \frac{\mathrm{WL_{it}}}{\widetilde{\mathrm{VA}}_{\mathrm{it}}}$. This is
   - partly directly observed from the data, for labor costs: WL_{it} in the numerator
   - partly estimated, for the corrected value added $\widetilde{\mathrm{VA}}_{\mathrm{it}}$ in the denominator. The aim of the correction is to retrieve that part of output (measured here by value added) that is anticipated by the firm. This is needed because we assume that firms minimize costs based on a "prediction" of value added i.e. they do not take into account unexpected shocks to production. The prediction is based on fitting a rich polynomial function of inputs on value added, capturing the anticipated part of output:

$$va_{it} = h(k_{\mathrm{it}}, l_{\mathrm{it}}, m_{\mathrm{it}}) + \nu_{c,j} + \eta_{t,j} + \epsilon_{\mathrm{it}},$$

   - where the function $h(.)$ contains all base effects and interactions containing first and second order terms in an additive way, following the code in the online Appendix by

De Loecker and Warzynski (2012). They compute the predicted level of value added as follows, which we also adopt:

$$\widetilde{VA_{it}} = \frac{VA_{it}}{\exp(\widehat{\epsilon_{it}})},$$

where $\hat{\epsilon}_{\mathrm{it}}$ is the residual obtained from the previous equation and VA_{it} is value added as observed in the data.

3. Deriving the markup μ_{it} as the ratio of the output elasticity of employment and the corrected wage share:

$$\mu_{it}^{(L)} = \frac{\hat{\beta}_L^j}{w\tilde{s}_{\mathrm{it}}}.$$

Deflation and currency conversion

Real values are obtained by applying two-digit industry value added deflators from detailed OECD National Accounts. This uses the ISIC Rev. 4 variant of the classification of activities. If deflators are missing at the two-digit industry detail, they are filled up by applying the growth rate in the price index at the immediate higher level of aggregation. For instance, if textile manufacturing (industry code 13) has missing information on the value added deflator for a particular country in a particular year, the growth rate from the immediate higher level (Textiles and wearing apparel, industry group 13-14) is used. If that is missing as well, then once more the immediate higher level (Textiles, wearing apparel, leather and related products industry group 13-15) is used. The same practice is followed for the other deflators used in the paper: gross output, value added, intermediate inputs and gross fixed capital formation. We use the country-industry level purchasing power parity database of Inklaar and Timmer (2014), see details therein for the trade-offs involved in deriving their PPP measures.

Filtering and cleaning

In order to limit the influence of erratic or implausible firm-behaviour, we exclude information for firms that report an extreme annual log-change (growth). More precisely, the variable is set to missing for the whole observed life of the firm if at least once, the variable has a growth rate that is in the top or bottom 1% of the growth distribution, at least once during their observed period. We do this procedure for the following variables: labor productivity measures, MFP measures, employment, capital, capital ratio, intermediates, value added and gross output. The rationale behind being relatively strict is that when a big growth rate – i.e. level shift – is observed, it is difficult to know whether the pre- or the post- shift period should be retained for the analysis. By removing the whole firm, we are also likely to exclude cases when a firm purchased another (relatively large) one as well as when a firm is being split-up. Put differently, this method ensures that firms undergoing major changes arising from mergers, acquisitions or spinoffs – which are outside the scope of this analysis – are excluded, even if their legal identifier in the underlying database remains unchanged.

Representativeness issues

A key drawback of Orbis is that it is a selected sample of larger and more productive firms and thus tends to under-represent smaller and younger firms in some economies. Accordingly, we exclude firms with less than 20 employees. Even so, the analysis of the MFP growth of laggard firms should be interpreted with particular caution, to the extent that laggards are likely to be less well represented in the sample.

While this issue is probably less of a concern for firms at the national and global frontier, some other issues remain. For example, the reporting unit (establishment or firm) may be different across countries. A related issue is that countries may apply different accounting requirements. For instance, US companies in Orbis report their financial statement in a consolidated manner, while in most European countries the database contains mainly unconsolidated accounts.[47] Accordingly,

[47] Working with a mix of the two types of accounts carries the risk of double counting certain activities if a firm files both consolidated and unconsolidated accounts. However, the aim of this paper is not to measure aggregate economic activity but to analyse the determinants of firms' behavior. Thus, the ideal reporting and consolidation level (i.e. group, firm or establishment) should be the one that most closely reflects managerial decisions. It is a difficult task to judge a priori which level that is, but most of the literature assumes it is either the firm or the group. For these reasons, we

the coverage of Orbis is less satisfactory for the United States than many European countries, although its coverage of US affiliates abroad is still good. Furthermore, multinational firms may systematically shift profits across the countries in which they have affiliates, depending on the tax system of the countries of its affiliates (see OECD 2013). A priori, it is not clear in which direction these factors will bias the analysis given that the focus is only on the global frontier and the gap relative to "all laggard firms" and thus country boundaries are less relevant. However, it is reassuring that the key result of Section 4 – i.e. that global frontier firms have become relatively more productive over the 2000s compared to other firms – is robust to excluding firms that are part of a multi-national group (i.e. headquarters or subsidiaries) where profit-shifting activity may be relevant. However, this comes at the cost of significantly reducing the number of observations, so it is not incorporated in the baseline specification but is instead presented as a robustness test (Appendix A, Figure A6).

Another caveat is that emerging market economies are not well represented in the database hence they are not included in our analysis. While this is unlikely to significantly affect the measurement of the global productivity frontier, it may have implications for diffusion if global frontier technologies are increasingly diffusing to firms in emerging markets but not to those in OECD economies. However, this seems unlikely, in light of the evidence presented in Comin and Mestieri (2018) which highlights impediments related to the penetration of new technologies across a sample of developed and developing economies alike.

The composition of countries in the frontier is probably still not entirely accurate, as the Orbis database has a low coverage of US company accounts that are suitable for productivity analysis (Gal, 2013). Nevertheless, as discussed in Andrews, Criscuolo and Gal (2015), firms located in the United States, and other highly developed countries, are well-represented in the global frontier grouping. Moreover, this definition of the global frontier seems to match anecdotal evidence with for example Finland and Korea having firms at the global frontier in most ICT sectors, or Italy being well represented at the global frontier in the textiles industry.

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give priority to consolidated accounts by removing the unconsolidated ones for companies where both types of accounts are present in the data.

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