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LAGGARD FIRMS, TECHNOLOGY DIFFUSION AND ITS STRUCTURAL AND POLICY DETERMINANTS

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BETTER POLICIES FOR BETTER LIVES

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Executive Summary

A growing body of literature has shown that the pervasive slowdown in productivity growth observed across many countries over the last decade has been accompanied by an increased divergence in productivity between high productivity firms and laggards (Andrews et al., 2016; Berlingieri et al., 2017b). Recent studies look at the characteristics of firms that operate at the global productivity frontier, and at their relationship with other firms in the economy (Andrews et al., 2015; Andrews et al., 2016). However, these studies are mainly focused on the distinction between top performing firms and the rest of the productivity distribution. Very little is known about the characteristics of firms that operate at the very bottom of the distribution and their growth performance over time. Even less is known about how their performance affects aggregate productivity (growth), and which structural factors and policies might help laggard firms close their productivity gap with the frontier.

To bridge this gap in the literature, this report uses the novel OECD MultiProd dataset, which is based on the full population of firms (or a representative re-weighted sample), to study more closely the left tail of the productivity distribution, i.e., "laggard firms". Laggards are defined as firms belonging to the bottom 40% of the productivity distribution in each country, industry and year.

Analysing the main characteristics of laggard firms and their contribution to aggregate productivity, this report highlights four main results:

- Laggards are on average smaller and younger than median firms, and represent a significant share (about 30%) of total employment.
- The composition of the group reflects firm dynamics and is related to business dynamism through firm entry and exit.
- Increasing the productivity of laggards to the level of the median firm (i.e., by about 60%) could, on average, increase aggregate productivity by roughly 6%.
- The productivity growth of laggards is on average higher than in the rest of the distribution. In line with neo-Schumpeterian growth theory, the report confirms the expected positive relationship between laggards' distance to the (national) frontier and their productivity growth, and additionally shows that this catch-up effect is more pronounced for younger firms.

These results have two key implications for the study of laggard firms and their contribution to aggregate productivity. Firstly, when focusing on the left tail of the productivity distribution, an analysis that goes beyond the concept of the "representative laggard firm" is particularly relevant to embrace the diversity of firms in this group. A direct implication is that one should be cautious in associating laggards with unhealthy firms, or "zombie firms", and even more so when advocating that low productivity firms should exit the market. Secondly, given the high share of entrants and young firms, laggards seem to matter for aggregate productivity and its future growth, as well as for employment growth.

Subsequently, the report provides additional evidence of a slowdown in the speed of catch-up, raising further concern of a "breakdown of the diffusion machine". The report then investigates the hypothesis that the transition to a digital and knowledge economy contributes to this slowdown by raising barriers to diffusion. The econometric analysis provides some evidence supporting this hypothesis, by showing that more digital and skill-intensive industries display lower rates of catch-up. This also

translates into higher levels of productivity dispersion in these industries. Investments in intangible ICT capital (software and database) and skills requirements seem to be particularly relevant for the speed of catch-up.

Various barriers associated with the transformation of the economy might hamper the diffusion of technology and knowledge. The lack of skills, the cost of investment in both ICT and complementary intangible assets, as well as the lack of absorptive capacity are potentially important obstacles. However, the report shows that policies may be efficient in removing these barriers and in lifting the bottom of the productivity distribution:

- Low levels of skill mismatch are linked to a higher speed of catch-up, while a higher share of under-qualified workers are linked to a slower catch-up. Empirical evidence suggests that lifelong learning – through training of working adults or through active labour market programs – has the potential to increase the speed of catch-up, especially in industries that are more digital or skill intensive.
- The report also suggests that more favourable financial conditions for SMEs, as reflected in the higher share of outstanding loans to SMEs and lower interest rate spreads between large and small firms, may help laggards catch up faster in more digital and skill intensive industries. This in turn indicates that relaxing financial constraints may help overcome the financial barriers to technology adoption. Relevant policies need to be shaped by the significant heterogeneity of laggard (and small) firms. Given that, especially in this context, one size does not fit all, relying on size contingent policies may not target correctly firms that could benefit from financial support.
- Direct government support to business expenditures on R&D is associated with faster catch-up. As direct funding of R&D projects through grants, subsidies or procurements may effectively raise firms' absorptive capacity, these might be more effective policies for firms with a growth potential to access support, rather than R&D tax credits.

The report also outlines a framework for an ecosystem of policies promoting diffusion. It discusses "demand-side" policies focusing on potential adopters, and emphasises the need to raise awareness about new technologies, their use and benefits, as well as to develop firms' absorptive and investment capacity, and ensure positive return to adoption while reducing associated risks and uncertainties. Insights from the literature on diffusion also motivate a discussion on "supply-side" policies that stimulate innovation and the development of suitable and affordable technologies. This would require a policy ecosystem that fosters the production and sharing of knowledge, and to enable experimentation.

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Last but not least: laggard firms, technology diffusion and its structural and policy determinants*

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Abstract

Using a unique dataset that collects micro-aggregated firm-level information on productivity in 13 countries over the 1994-2014 period, this paper provides new evidence on the main characteristics of laggard firms and their potential for productivity growth. It finds that laggards, defined as firms in the bottom 40% of the productivity distribution, are on average younger and smaller, and play a large role in the process of aggregate resource reallocation and firm dynamics. The report further analyses the impact of firms' features and structural factors on the catch-up potential of laggards. Results show that younger laggard firms converge faster, suggesting that the composition of the laggard group has implications for future productivity. At the same time, laggards are converging at a slower rate in highly digital- and skill-intensive industries, suggesting the presence of barriers to technology and knowledge diffusion. This result could help explain the much-debated productivity slowdown and the increase in productivity dispersion that the global economy has seen in recent years. This report also finds that policies aimed at improving workers' skills, alleviating financial constraints to investments and increasing firms' absorptive capacity through direct R&D support can accelerate the diffusion of knowledge and technology, and help laggard firms to catch up.

Keywords: Productivity, Laggards, Catch-up.

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1. Introduction

The role played by productivity in the success of firms and, ultimately, in the prosperity of countries is very well known. A vast literature suggests that differences in aggregate productivity are the main drivers of international income differences found both across countries and over time (for instance, Prescott, 1998; Klenow and Rodriguez-Clare, 1997).[1] However, aggregate productivity growth slowed in many OECD economies over the past decade. This phenomenon has raised concerns that there may be structural dimensions to the slowdown, and has ignited a spirited debate on the future of productivity.

Economists addressing this puzzle have been divided on the nature of the decline of productivity growth, suggesting several explanations. In particular, some argue that the speed of innovation, one of the main engines of productivity growth, is slowing down, or that new technologies do not have the potential to raise productivity as past innovations did (Gordon, 2012). Others draw a more optimistic picture of the future of productivity, suggesting that some of the new technologies have the potential to bring disruptive innovations, favour sustained growth and be truly transformative, but time is needed for new technologies to convert into productivity gains because of adoption lags, adjustment costs, and the need for complementary investments in intangible assets and infrastructure that are costly to replicate (Brynjolfsson and McAfee, 2012; Brynjolfsson et al., 2017).

A first step to partially overcome these conflicting views is to look beyond aggregates. Aggregate productivity growth, in fact, depends closely on firm-level performance and the allocation of resources to firms with different performance. In turn, empirical evidence finds substantial heterogeneity in productivity across firms, even within narrowly defined industries (Syverson, 2004). In light of the large dispersion of firms' productivity, analysing industry aggregates or looking at the "average firm" does not offer the complete picture: countries might display the same average but very different underlying distributions, i.e., they could have a long tail of low performing firms that might represent a significant drag on productivity. This fact has important policy implications. For instance, low average productivity can be explained by either too few firms at the top (lack of innovation), or too many firms at the bottom (weak market selection or lack of opportunities and investment), two different situations that would require very different policies. To better design policy strategies, it is therefore essential to understand how firm-level productivity patterns translate into aggregate productivity growth.

Recent contributions have emphasised that, when looking at micro-level data, productivity heterogeneity has increased over time: the slowdown in productivity growth has been accompanied by an increased divergence in productivity between highly productive firms and laggards (Andrews et al., 2016; Berlingieri et al., 2017b). This increased productivity gap might seem surprising in light of Neo-Schumpeterian growth models, which predict that firms lagging behind should grow faster by learning from the best (Aghion and Howitt, 2006; Acemoglu et al., 2006). According to these models productivity growth depends on two main factors: the distance to the productivity frontier, and the ability to learn from the productivity frontier. One possible explanation for this rising productivity gap between the frontier and other firms is that technologies and knowledge developed at the frontier do not diffuse to all firms rapidly enough. In other words, new technologies developed at the global frontier may spread at a slower pace to non-frontier firms, and many existing technologies may remain unexploited by a large share of firms in the economy (Comin and Mestieri, 2018).

Recent studies look at the characteristics of firms that operate at the productivity frontier and their relationship with other firms in the economy, as well as at the possible policies that facilitate the diffusion of productivity gains (Andrews et al., 2015; Andrews et al., 2016). However, they mainly focus on the distinction between top performing firms and the rest of the productivity distribution. Very little is known about the characteristics of firms that operate at the (very) bottom, their growth performance over time (both in absolute terms and relative to frontier firms), and their contribution to aggregate productivity growth. The literature focusing on the least productive firms is still scant, often due to the lack of representative data for this group of firms. Berlingieri et al. (2017b), however, show that in the last decade productivity divergence has been more pronounced in the lower tail of the productivity distribution than at the top, suggesting that laggards might have experienced a more severe slowdown in the speed of diffusion of technologies with respect to other firms in the economy. This calls for further investigation of the characteristics of firms at the bottom of the productivity distribution, their contribution to aggregate productivity growth and the determinants of their performance.

This report contributes to bridge this gap in the literature by studying more closely the left tail of the productivity distribution, i.e., laggard firms. It highlights some essential characteristics, notably that they are younger and smaller, but also emphasises the heterogeneity of this group. Firms can be at the bottom of the productivity distribution for different reasons. They might be: i) low productivity firms that would typically exit in a competitive market, the so called "zombie firms" (Caballero et al., 2008; Adalet McGowan et al., 2017); ii) SMEs that by the nature of their activity or purpose have a limited scope for productivity and size growth; iii) firms entering the economy, which are likely to operate below their efficiency scale during the first stage of their development and have significant growth potential.[2]

Understanding the characteristics of laggards and acknowledging the heterogeneity of this group has particularly important policy implications. First, policies aiming at fostering productivity growth of laggards to address the productivity divergence at the bottom may be particularly efficient. Additionally, laggards' characteristics imply that they may be more responsive to policies and less likely to "game the system", as recent evidence on the effect of industrial policies shows (Criscuolo et al., 2019). A relevant policy implication of the heterogeneity of laggards is that one size does not fit all, and targeted supports based on simple rules (such as size contingent policies) may not be appropriate for all laggard firms. In addition, this report shows that, in order to effectively promote convergence through knowledge and technology diffusion, not all policies need to be targeted to a specific group of firms (consider, for example, lifelong learning policies). A third implication is that fostering productivity growth at the bottom may be beneficial along several dimensions. First, supporting productivity growth at the bottom may trigger scale-up dynamics, which can deliver significant employment gains given that young firms – a constitutive part of the laggard group – contribute disproportionately to employment growth (Haltiwanger et al., 2013, Criscuolo et al., 2014, Criscuolo et al., 2017). Such policies could also particularly benefit local employment and development, a positive outcome for inclusive growth. Another positive outcome for inclusive growth is related to the potential effect on wage inequality that policies addressing productivity divergence could have. Berlingieri et al. (2018b) show that lower productivity is associated with lower wages for workers: wages of the worst performing firms (bottom 10% of the productivity distribution) are roughly half of those in the median productivity firm. Given that a significant share of workers are employed in low productivity firms (in our sample around 25-30% of workers are employed in the 40% least productive firms), it is of utmost importance to analyse this group of firms to better understand what are the appropriate policy interventions to foster their productivity growth and, consequently, wage growth.

Motivated by the positive outcomes that could be obtained by lifting the bottom of the productivity distribution, this report investigates the characteristics of laggards, the possible drivers of reduced diffusion that might weigh on their productivity growth, and policies that can help restore the diffusion machine. It highlights three policy levers that may effectively promote knowledge and technology diffusion. Firstly, increasing the level of skills in the population through education and training policies may enhance firms' absorptive capacity and encourage faster adoption of new technologies and good business practices. Secondly, financial constraints are a possible barrier to diffusion. Policies that alleviate such constraints for laggards may encourage them to carry out investments in new technologies, as well as complementary investments that are necessary for catching up. Finally, public government support to R&D (through direct funding of business R&D expenditures) seem to have the potential to enhance laggards' absorptive capacity. The report also discusses the role of other policies and advocates an ecosystem of policies to support diffusion along several dimensions, focusing on both potential adopters and innovators, that also play a role in the diffusion of innovation.

To analyse the characteristics of laggards, the structural determinants of knowledge diffusion and the policies that can foster it, the report uses a novel data source, the OECD MultiProd dataset, which is based on the full population of firms (or a representative re-weighted sample) in most sectors of the economy. This feature is particularly important for the purpose of this work: MultiProd is one of the few datasets to include the population of firms for such a large number of countries and, hence, suitable for a cross-country analysis on laggards. It collects micro-aggregated firm-level data on different features of the productivity and wage distribution for the entire economy in more than 25 countries over the period 1994-2014. This report focuses exclusively on the 13 countries for which information on the whole population of firms is available in manufacturing and non-financial market services.[3] "Laggards" are then defined as the firms belonging to the bottom 40% of the productivity distribution in each 2-digit industry and year. More specifically, two different groups of the productivity distribution are taken into consideration: i) 1st to 10th, and ii) 10th to 40th percentiles of the productivity distribution. Two different measures of productivity are used in the report: labour productivity (LP, henceforth), and multi-factor productivity (MFP, henceforth).

The report starts by analysing the main characteristics of laggards: they are on average smaller and younger than the average, and employ 25–30% of workers. Moreover, a decomposition of their performance and their contribution to aggregate growth (Melitz and Polanec, 2015) shows that laggards are characterised by a very dynamic environment: they exhibit a higher rate of entry, exit and reallocation of resources with respect to the rest of the distribution. This result suggests that when focusing on the left tail of the productivity distribution an analysis that goes beyond the concepts of "representative laggard firm" or "zombie firm" is required, and that it is important for policy to consider the wide heterogeneity.

Although laggards do not necessarily represent a large portion of the economy from a static point of view, they are very relevant from a dynamic point of view. A counterfactual exercise shows that (labour) productivity would increase by 6% if the (labour) productivity of laggards was hypothetically equalised to that of the central part of the productivity distribution. In addition, this report shows that low productivity firms grow faster (in terms of productivity) than firms in the middle or the top segment of the distribution. This result is in line with models of competitive diffusion (e.g., Jovanovic and MacDonald, 1994) and with the neo-Schumpeterian growth theory (e.g., Aghion and Howitt, 2006, and Acemoglu et al., 2006) which implies productivity convergence.

The catch-up of laggard firms is further explored applying a methodology similar to Griffith et al. (2004) and Bartelsman et al. (2008), i.e., looking at the relationship between productivity growth and the distance to the frontier (the productivity gap). Based on a theoretical and an empirical framework to look at the catch-up of laggards, the report investigates the role of some structural factors and policies affecting catch-up. Notably, for this analysis the frontier is defined at the national level, as the top 10% most productive firms in each country-2 digit industry-year. It has been shown that productivity growth of laggard firms is more strongly related to the productivity of the most advanced domestic firms as opposed to the global frontier, often composed of foreign firms (Bartelsman et al., 2008, Iacovone and Crespi, 2010). For the purposes of this report it seems therefore more important to focus on the national frontier rather than the global one. The analysis controls for the potential growth of each industry, which captures the fact that firms belonging to different industries might have different potential growth rates.

Interestingly, the expected positive relationship between the productivity gap and the productivity growth of laggards in fact depends on firm and industry characteristics. The report establishes that this positive catch-up effect is stronger for young firms. On the contrary, the catch-up happens at a slower rate in more digital and skill-intensive industries. This points to the existence of potential barriers to technology and knowledge diffusion related to the digital transformation and the transition to a knowledge economy. The existence of increasing barriers may help explain the breakdown of the diffusion machine that is documented in this report as well as in the literature (Andrews et al., 2016, Akcigit and Ates, 2019a). This decline in the speed of knowledge diffusion may weigh on aggregate productivity growth, but could also have broader macroeconomic consequences. Akcigit and Ates (2019a) and Akcigit and Ates (2019b) identify the decline in knowledge diffusion as one of the main driving forces behind the widening productivity dispersion, the increase in market concentration, the decline in business dynamism and the labour share decline. Taken together, the results presented in this report suggest that the transition to a digital and knowledge economy, although potentially beneficial for overall growth, may not benefit all firms equally. These results add to recent evidence on the heterogeneous effects of the digital transformation on firm productivity. In particular, they are line with evidence that differences in firms' capabilities and incentives induce heterogeneity in adoption of digital technologies (Andrews et al., 2018), so that more productive firms benefit more from the digital transformation (Gal et al., 2019). Despite these barriers to technology and knowledge diffusion, appropriate policies may alleviate the negative effects associated with this transformation, and could ensure that its benefits are shared more widely.

There is significant scope for policies to increase the speed of diffusion and the penetration of new technologies. Firstly, the report provides empirical evidence that seems to confirm the relevance of three policy areas whose importance has been highlighted in the literature on diffusion, namely the role of human capital, financial barriers and R&D. Secondly, the report also advocates for an ecosystem of policies that could shape the incentives and capabilities of potential adopters, but also favour innovation and development of suitable and affordable technologies.

The econometric analysis focuses on three areas where policies may have a direct effect on adoption. First, the skill mismatch related to the changing set of necessary skills should be addressed. Results indicate that monitoring the level of workers' under-qualification is of primary importance. Results also indicate that a higher incidence of training is associated with faster catch-up of laggards, particularly in industries with higher skill requirements. Policies carefully designed to promote learning among low-skilled adults seem a promising way to stimulate the diffusion of knowledge and the adoption

of new technologies. In addition, policies may foster adoption by helping laggards overcome financial barriers to profitable investments in ICT technologies. Due to imperfect financial markets laggards are likely to face stronger barriers to the financing of investment in tangible and intangible capital. Finally, it seems that government support to R&D through direct financing of business expenditures in R&D has the potential to booster diffusion of knowledge, suggesting that it can effectively expands firms' absorptive capacity and support the continuous process of innovation necessary for diffusion.

The report also relies on existing evidence and insights from diffusion models to outline a policy framework that accounts for the wide range of factors shaping the diffusion process, and advocate for an ecosystem of policies that comprehensively address the lack of diffusion. This framework is based on the distinction between "demand-side" and "supply-side" policies. Demand-side policies focus on potential adopters, and should aim at: increasing awareness about technologies; raising the absorptive and investment capacity of laggards; and, ensuring that successful adopters can reap the benefits of their digital transformation, while at the same time reducing the risks and uncertainties associated with adoption. Supply-side policies may also facilitate diffusion by promoting radical innovation and secondary inventions necessary to bring technologies to the market and make them affordable to everyone, including laggards. This requires policies supporting productivity enhancing innovation and, thus: fostering the production and sharing of knowledge and enabling experimentation.

The rest of the report is organised as follows: Section 2 describes the data sources and the productivity measures used for the analysis. In Section 3 the main characteristics of laggard firms are presented, and the importance of laggards for aggregate productivity is investigated. Section 4 reviews an empirical framework to evaluate convergence forces triggered by a catch-up effect, and to evaluate some factors possibly affecting convergence. Section 5 confirms the expected catch-up effect at the bottom of the productivity distribution and shows that it is stronger for young firms. Then, it discusses a slowdown in diffusion and investigates the existence of possible barriers to diffusion related to the digital transformation and the transition to a knowledge economy. Section 6 looks at the role of specific policies in shaping catch-up of laggards, and outlines a framework for policy recommendations to stimulate diffusion. Finally, Section 7 concludes.

2. Data

This section provides an overview of the data used, present the main measures of labour and multi-factor productivity, as well as the definition of "laggard" firms adopted in this work. Further details on the MultiProd project and the methodology adopted can be found in Desnoyers-James et al. (2019) and Berlingieri et al. (2017a) .

2.1. The MultiProd dataset

The analysis conducted in this report relies on the work undertaken in the last few years within the OECD "MultiProd" project. The implementation of the MultiProd project is based on a standardised STATA® routine that micro-aggregates confidential firm-level data from production surveys and business

registers, via a *distributed microdata analysis*. This methodology was pioneered in the early 2000s in a series of cross-country projects on firm demographics and productivity (Bartelsman et al., 2005; Bartelsman et al., 2009). The OECD currently follows this approach in three ongoing projects: MultiProd, DynEmp, and MicroBeRD.[4] The distributed micro-data analysis involves running a common code in a decentralised manner by representatives in national statistical agencies or experts in governments or public institutions who have access to the national micro-level data. The centrally designed, but locally executed, program codes generate micro-aggregated data, which are then sent back for comparative cross-country analysis to the OECD.

The advantages of this novel data collection methodology are manifold. It puts a lower burden on national statistical agencies and limits running costs for such endeavours. Importantly, it directly uses national micro-level representative databases, while at the same time achieving a high degree of harmonisation and comparability across countries, sectors, and over time.

The MultiProd program relies on two main data sources in each country. First, administrative data or production surveys (PS), which contain all the variables needed for the analysis of productivity but may be limited to a sample of firms. Second, business registers (BR), which contain a more limited set of variables but for the entire population of firms. The BR is not needed when administrative data on the full population of firms are available. When data come from a PS, however, the availability of the business register substantially improves the representativeness of results and, thus, their comparability across countries.[5]

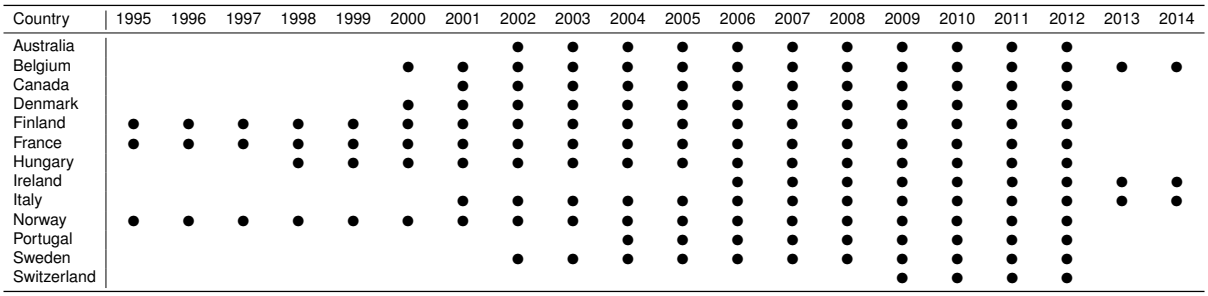
Census and administrative data, indeed, normally cover the whole population of businesses with at least one employee. Still, these datasets do not always exist or include all the information needed to calculate productivity. In these cases PS data need to be used. One of the big challenges of working with firm-level production surveys is that the selected sample of firms might yield a partial and biased picture of the economy. Whenever available, BRs, which typically contain the whole population of firms, are therefore used in MultiProd to compute a population structure by year-sector-size class. This structure is then used to re-weight data contained in the PS in order to construct data that are as representative as possible of the whole population of firms and comparable across countries.

At the time of writing, 24 countries have been successfully included in the MultiProd database (namely, Australia, Austria, Belgium, Brazil, Canada, Chile, Costa Rica, Denmark, Finland, France, Germany, Hungary, Indonesia, Ireland, Italy, Japan, Luxembourg, The Netherlands, Norway, New Zealand, Portugal, Sweden, Switzerland, and Viet Nam). For most countries the time period spans from early 2000s to 2012. For Chile, Austria and Switzerland the time horizon is shorter (starting in 2005, 2008 and 2009 respectively), whereas for Finland, France and Norway data are available at least since 1995. For further details about the data coverage and its representativeness, see Desnoyers-James et al. (2019).

MultiProd collects data for all sectors of the entire economy, whenever available. However, for the purposes of this analysis the sample is restricted to manufacturing and non-financial market services.[6] In addition, in order to guarantee the comparability across deciles of the productivity distribution and across macro-sectors, the sample is further restricted to those countries providing productivity statistics for both manufacturing and non-financial market services, and not imposing any threshold for inclusion of firms in the sampling frame. This last aspect is particularly important for the purpose of this report: given its focus on the bottom part of the productivity distribution, it is important to include in the sample

only countries where the whole distribution of firms is well represented. The final sample includes 13 countries (namely, Australia, Belgium, Canada, Denmark, Finland, France, Hungary, Ireland, Italy, Norway, Portugal, Sweden and Switzerland). Table 1 details the years covered for each country.

Table 1. Years covered in the MultiProd dataset



The statistics collected in the MultiProd database are computed at various levels of aggregation and using different breakdowns. This report is based on statistics aggregated at the industry level and further decomposed into five groups of firms corresponding to how productive they are, i.e., different parts of the productivity distribution have been split into: the very bottom, the bottom, the median group, those above the median but not at the frontier, and the frontier firms (corresponding respectively to 1st to 10th, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th percentiles of the productivity distribution). This particular breakdown of the data is the main source of information for this report, and allows us to characterise more precisely firms with different levels of productivity, as well as their dynamics.

Table 2 displays summary statistics in terms of the firm's average number of employees, average age, as well as the share of total employment for the different groups of firms mentioned above. Only manufacturing and non-financial market services are taken into account. This table highlights some interesting facts and provides a first and simple appraisal of the characteristics of firms according to their labour productivity (LP) performance. The firm's average number of employees increases with LP, indicating that more productive firms are on average bigger in terms of employment. As such, the relative contribution of each group to aggregate employment rises with the LP group. The bottom 10% of firms account for 6% of employment, the top 10% accounts for 14%.[7] Age is homogeneously distributed, with the exception of the bottom part of the productivity distribution where firms are on average younger. Stated differently, the bottom half of the productivity distribution includes firms which are smaller and younger than the average, but still represents a large portion of total employment: the 40% of firms with the lowest productivity still account for almost 30% of employment, on average, in manufacturing and non-financial market services.[8]

Table 2. Employment and age distribution by labour productivity (LP) performance groups

Productivity group	% Firms	Avg. Age	Avg. Firm size	% Employment
Very bottom [p(0-10)]	10%	10.89	11.81	5.91
Bottom [p(10-40)]	30%	13.18	18.89	23.79
Median group [p(40-60)]	20%	14.5	29.7	19.71
Above the median [p(60-90)]	30%	15.2	50.35	36.18
National frontier [p(90-100)]	10%	14.82	68.14	14.42

Note: Numbers are averages across countries and years. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Due to censoring on the firm birth year variable in some countries, the table reports average age based on 7 countries only: BEL, DNK, FRA, IRL, ITA, NOR, SWE.

2.2. Measures of productivity

The report relies on two measures of productivity, labour productivity (LP) and multi-factor productivity (MFP). LP is a widely used productivity measure in the literature and aims at capturing the amount of output produced by a firm for a given amount of labour input. It is computed at the firm level as the (real) value-added per worker:

$$\text{LP_VA}_{it} = \frac{VA_{it}}{L_{it}}, \tag{1}$$

where VA_{it} is the value-added of firm i at time t, and L_{it} is its employment.[9] The advantage of this measure is that it is widely available, and fairly immune to measurement error. Moreover, it can be easily aggregated into sectoral-level or country-level LP using employment weights.

One of the main drawbacks of LP is that it does not quantify the impact of other inputs, such as physical capital or intermediate inputs. However, for some policy questions, it might be important to disentangle which inputs are actually driving LP. In order to properly address these issues and provide a more robust analysis, this study also exploit a measure of multi-factor productivity. This productivity measure accounts not only for labour but also for capital inputs, and should also better reflect productivity growth related to technological progress and diffusion of innovation.

To this aim, this study uses one of the various MFP measures contained in the MultiProd dataset. Specifically, the measure of MFP used in this report is estimated econometrically at the firm-level using the Wooldridge (2009) control function approach with value added as a measure of output. More technically, firms are assumed to have a Cobb-Douglas production function, but not necessarily constant returns to scale:

$$Y_{it} = A_{it} K_{it}^{\beta_K} L_{it}^{\beta_L}, \tag{2}$$

where A_{it} is the firm i's MFP at time t. It is typically unobserved and, therefore, it has to be estimated. The Wooldridge (2009) procedure relies on estimating variable inputs with a polynomial of lagged inputs and a polynomial of intermediates. It allows for the identification of the variable input and yields consistent standard errors.[10]

The dataset has been split into five productivity performance groups, i.e., five groups of the productivity (either LP or MFP) distribution: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. The number of productivity groups is constrained by confidentiality requirements, which impose a minimum number of observations in a cell (detailed at the country, 2-digit industry, year, and productivity group level). While this might impose some restriction on the definition of laggard firms, this pre-defined split also provokes a clear and harmonised definition of laggards across countries, and maximizes the information available by avoiding data suppression due to confidentiality requirements.

2.3. Definition of "laggard" firms

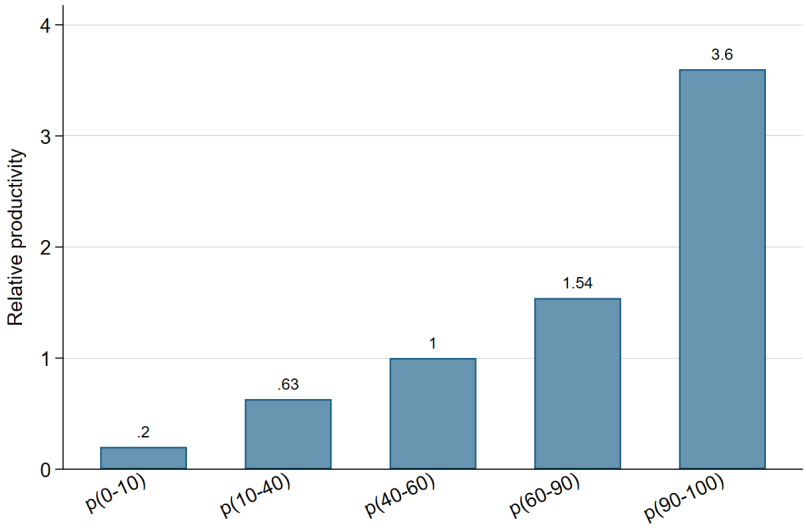
Most of the recent literature studying the productivity puzzle and the increased dispersion in productivity has focused on "frontier" firms, often defined as the top 5% of firms with the highest productivity at the global level (e.g., Andrews et al., 2016; Haldane, 2017 for the UK), as opposed to "laggards", defined as firms outside the frontier group. This report analyses the productivity distribution within each country and 2-digit industry, and focuses its attention on the left tail of the productivity distribution, i.e., the worse

performing firms in terms of productivity in a given country-industry-year. Therefore, a more focused definition of "laggards" is adopted.

In this report "laggard" firms are defined as the 40% least productive firms, i.e., firms belonging to the bottom 40% of the productivity (either LP or MFP) distribution in each country and 2-digit industry. More specifically, two different groups of the productivity distribution are taken into consideration: i) 1st to 10th, and ii) 10th to 40th percentile of the productivity distribution. This is made possible by the richness and uniqueness of the MultiProd dataset. MultiProd is , up to our knowledge, one of the few datasets to include the population of firms for a large number of countries and, thus, to be highly representative of all parts of the productivity distribution. This peculiarity makes it particularly suitable to analyse the bottom part of the productivity distribution, and justifies the more restrictive definition of laggard firms that is adopted in this report. This is also particularly relevant given that most of the reallocation process through firm entry and exit seems to occur in the very bottom part of the productivity distribution, as shown in Section 3.

Figure 1 (Figure C.1 in the Appendix) plots the employment-weighted average LP (MFP) in each group relative to the median group, and illustrates how far laggard firms are from the rest of the firms in terms of LP (MFP). It shows that the average productivity of firms belonging to the bottom 10% is around one fifth of the median productivity group. Firms belonging to the p(10-40) group exhibit instead a productivity which is roughly 60% that of firms belonging to the next group. Figure C.2 and Figure C.3 in the Appendix also plot the relative productivity of firms in different productivity groups for each country individually, pointing to some heterogeneity across countries.

Figure 1. Average LP by LP group relative to the median



Note: The figure plots the weighted average labour productivity in different groups of the productivity distribution with respect to the median group. In particular, the LP distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE.

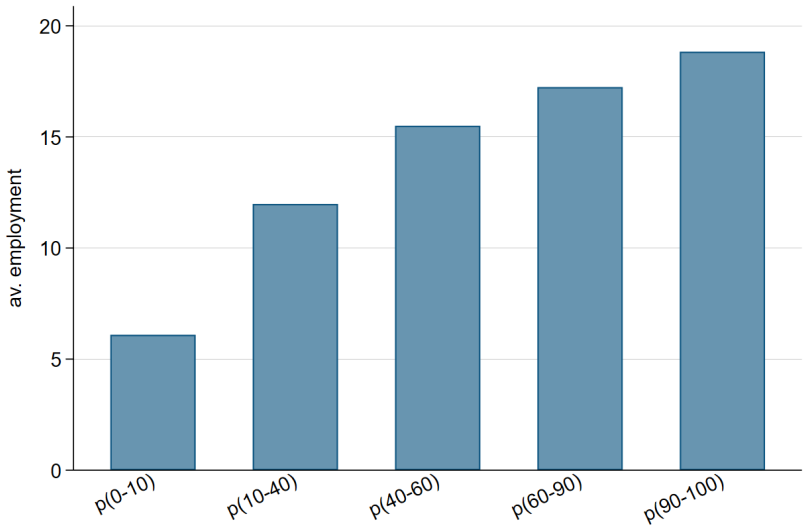
3. Characteristics of laggard firms

This section explores in more detail the main characteristics of laggard firms.[11] This descriptive analysis helps understand whether, and to what extent, firms belonging to the bottom of the productivity distribution are different from the rest. In turn, this characterisation may be informative of the nature of their productivity gap, and contribute to the design of more targeted economic policies.

3.1. Age and size

Firms' age and size are probably the most natural characteristics to explore when looking at differences among firms with different productivity levels. The literature predicts a positive correlation between size and productivity, at least in the manufacturing sector (e.g., Melitz, 2003 and Berlingieri et al., 2018b), as well as between age and productivity (Jensen et al., 2001). Figure 2 and Figure 3 confirm these predictions for labour productivity, showing that on average firms at the bottom of the productivity distribution are smaller and younger. In particular, firms in the middle of the productivity distribution (the median productivity group) are on average 2.5 times bigger than those at the very bottom, and 1.3 times those in the p(10-40) percentile.[12] Moreover, laggards are on average roughly two years younger than the median firm.[13] Similar results for MFP can be found in the Appendix (see Figure C.4 and Figure C.5).[14]

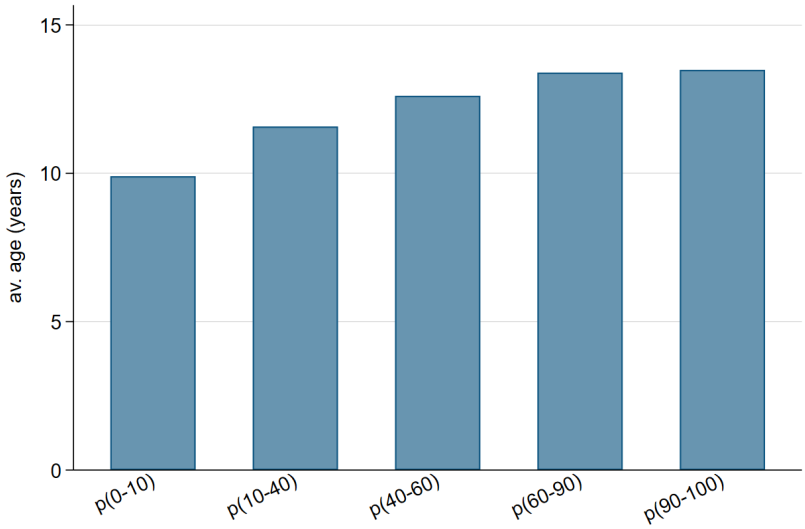
Figure 2. Average size by LP performance groups



Note: The figure plots the average (employment) size in different groups of the productivity distribution. In particular, the LP distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE.

These predictions are also confirmed in a regression framework for both LP and MFP when systematic differences within country-industry-year are taken into account, as shown in Table D.6 of the Appendix. For both LP and MFP, these regressions confirm that laggards are on average younger and smaller when compared to more productive firms in the same country, 2-digit industry and year.[15]

Figure 3. Average age by LP performance groups



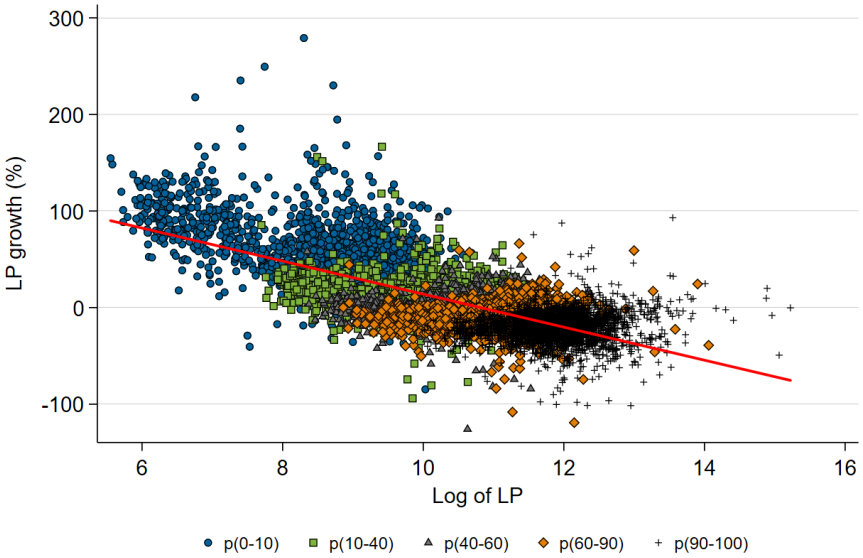
Note: The figure plots the average age in different groups of the productivity distribution. In particular, the LP distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only. Countries included: BEL, DNK, FRA, IRL, ITA, NOR, SWE.

This is a key point to understand the nature of these low productivity firms. Firms might end up being at the bottom of the productivity distribution for different reasons. They might be: i) low productivity firms that would typically exit in a competitive market, the so called "zombie firms" (e.g., Caballero et al., 2008, Adalet McGowan et al., 2017); ii) SMEs that by the nature of their activity or governance (or a lifestyle choice) are likely to remain small and have limited scope for productivity growth (e.g., local services); iii) firms that are hit by a temporary negative productivity shock; but also iv) firms entering the economy, which are likely to operate below their productivity potential during the first stage of their development.[16,17] Therefore, the averages displayed in the previous figures, although failing to represent the great heterogeneity among firms at the bottom, illustrate a key point for the analysis of laggards: the low tail of the productivity distribution is partly composed of young and small firms with a potential for growth.[18]

This potential for growth is further illustrated in Figure 4, which plots the correlation between the average productivity growth and the average level of (initial) productivity, within a country, 2-digit industry, and productivity performance group for each year. The figure highlights a negative relationship between the average productivity and the productivity growth rate of firms. Figure C.6 in Appendix shows that the same negative correlation is found in all countries of the sample. It suggests that in every country of the sample lower productivity is associated with faster growth.[19] The fact that less productive firms grow faster is in line with the neo-Schumpeterian growth theory (e.g., Aghion and Howitt, 2006, and Acemoglu et al., 2006) and with models of competitive diffusion (e.g., Jovanovic and MacDonald, 1994), which predict (conditional) productivity convergence: laggard firms should grow faster, given the larger stock of unexploited technologies and knowledge that they can readily implement.

Each above-mentioned type of laggards has very different welfare implications and would call for different policy responses. A direct implication of this heterogeneity is that one should be cautious in associating laggards with unhealthy firms, and more so when advocating that low productivity firms should exit the market. It is true that some "zombie firms" may crowd-out resources for other firms,

Figure 4. Average labour productivity and within firm labour productivity growth



Note: The figure plots the correlation between the average initial level of labour productivity at time *t* and the average firm-level productivity growth between *t* and *t+1*, within a country-industry-productivity group-year cell. The productivity distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE.

reducing the efficiency of resource allocation. However, some of the laggards with limited scope for growth, such as some family businesses, may still support employment, in particular for workers with lower than average employability and in lagging regions. Moreover, a significant share of laggards have the potential to grow and to contribute to future productivity growth.[20] Therefore, the concept of "representative firm" among laggards needs to be taken with a pinch of salt, in light of the fact that laggards may range from old firms with ageing technologies to young firms and entrants with a potential for productivity growth through innovation and technology adoption.

3.2. Firm dynamics and the productivity distribution

In order to more formally link the left tail of the productivity distribution with firm dynamics, this report adopts a dynamic decomposition of aggregate productivity (both LP and MFP) growth following Melitz and Polanec (2015) (described in more detail in Box 1). In this decomposition, the aggregate productivity growth is decomposed into the following components: the contribution of incumbent firms, both via the change in (unweighted) average productivity of incumbents and the change in the efficiency of resource allocation (i.e., did more productive incumbents grow more?), and the contributions of entering and exiting firms.[21]

Box 1 A dynamic decomposition of aggregate productivity growth

In each productivity group q, 2-digit industry j and year t, productivity growth is decomposed as follows[22] :

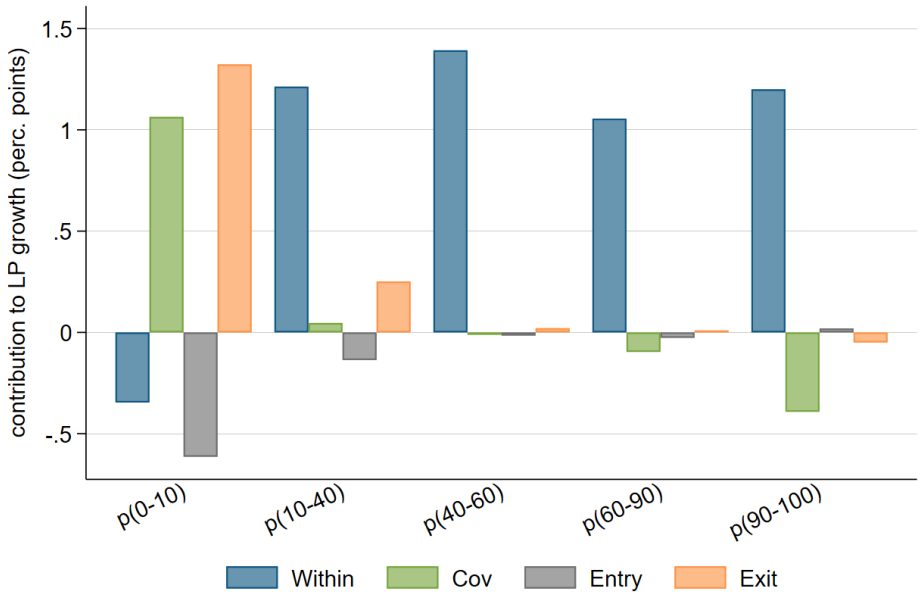
$$\begin{aligned} \Delta P_{qjt} &= \frac{1}{N^C}\sum_{i\in C}(P_{iqjt}-P_{iqjt-1}) + \Delta\underset{i\in C}{\text{Cov}}(\theta_{iqjt},P_{iqjt}) + \left(\sum_{i\in E}\theta_{iqjt}\right).(P^E_{qjt}-P^C_{qjt}) + \\ &+ \left(\sum_{i\in X}\theta_{iqjt-1}\right).(P^C_{qjt-1}-P^X_{qjt-1}) \end{aligned} \tag{3}$$

The first term is the change in the unweighted productivity average (P_{iqjt}) of incumbents firms (C) belonging to the productivity group q. The second term is the change in the Olley and Pakes (1996) covariance term computed for incumbents, i.e., the change in the covariance between size θ_{iqjt} (employment for the decomposition of LP growth, value added for the decomposition of MFP growth), and firms' productivity.[23] This term measures the contribution of the resource reallocation between incumbents to aggregate productivity growth (and in our case it also captures the contribution of incumbents that enter and exit each productivity group). Finally, P^E_{qjt}, P^C_{qjt}, P^X_{qjt-1} are the weighted productivity averages of, respectively, market entrants, incumbents, and market exiting firms of the group q computed in the relevant time period and with weights that sum up to one within each group.

As shown in Figure 5 (plotting the results of this decomposition in each LP group) and as explained below, the main message from the decomposition is that entrants and exiting firms transit through the group of laggards when entering and exiting the economy. This suggests that at the bottom productivity growth reflects mainly firm dynamics. Entry and exit are indeed significant components of productivity growth in the bottom tail of the productivity distribution, whereas in the rest of the distribution they play a very marginal role. In addition, the reallocation term seems to matter the most in the bottom 10%. These contributions to productivity growth at the bottom contrast with the contributions in the rest of the distribution (from the 10$^{\text{th}}$ percentile onward), where the most important component is by far the growth of the average productivity of incumbents, which, therefore, also drives total productivity growth. Overall, the positive contribution of exit reveals that firms exiting the economy are generally less productive than the average surviving firms, in line with the process of market selection. In the same way, the negative contribution of entry suggests that newly created firms are also less productive than surviving ones.[24] The same decomposition to each group of the MFP distribution (see Figure C.7 in the Appendix) yields very similar results and, therefore, confirms the importance of firms dynamics and reallocation at the bottom of the productivity distribution.[25]

In a related study, Hyytinen and Maliranta (2013) analyse the contribution of entry, exit, reallocation and incumbents over the firm life-cycle by applying a comparable decomposition to firms belonging to different age groups. Interestingly, this study finds a positive contribution of exit to productivity growth for exiting firms in all age groups, stressing that exiting firms are less productive than other firms regardless of the age at which exit occurs.[26] Therefore, the positive contribution of exit displayed in Figure 5 seems to reflect both the market selection of young firms that exit before closing their productivity gap, and the exit of old, low productivity incumbents transitioning through the group of laggards before exiting the market.[27]

Figure 5. Melitz and Polanec decomposition by LP performance group



Note: The figure plots the Meliz and Polanec decomposition in different groups of the productivity distribution. In particular, the LP distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. The bars of this figure are computed in the following way: first gains are aggregated across industries within country and productivity groups using employment shares of the industry in the economy. Subsequently, a simple average is computed across years within each country-productivity group. Finally, the median is computed over countries, separately for p(0-10) and p(10-40). Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE.

Overall, Figure 5 and Figure C.7 (in the Appendix) highlight the peculiarities of the bottom part of the productivity distribution, i.e., a more diverse environment in terms of firms' characteristics and the higher importance of entry, exit and reallocation of resources with respect to the rest of the distribution. This result confirms that when focusing on the left tail of the productivity distribution, an analysis that goes beyond the concept of a "representative firm" is useful. A "representative laggard firm" cannot be properly identified without sacrificing too many pieces of the complex picture outlined for the least productive firms.

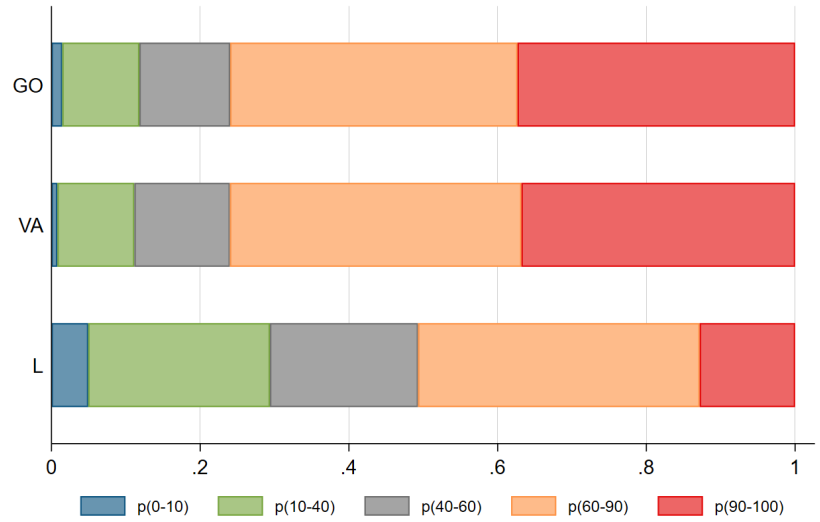
The lack of representative laggard firms is an important and challenging reality for policy makers. The heterogeneity of laggards implies that targeting the right firm is quite complex. Such targeting appears indeed more difficult than in the upper part of the productivity distribution, where some categories of firms may be more easily identified (e.g., R&D intensive, MNE, etc). At the same time, different policy responses may be needed for different categories of laggards. This challenge is, however, of primary importance given the potential of some of these firms for the future of productivity. The rest of this section estimates the contribution of laggards to aggregate productivity.

3.3. Contribution to aggregate productivity

Laggard firms represent a relatively small share of the economy both in terms of employment, value added, and gross output (Figure 6 and Table D.7 for LP; Figure C.8 and Table D.8 for MFP). Overall, firms belonging to the bottom 40% of the LP (MFP) distribution represent around 31% (25%) of total

employment, 12% (15%) of value added, and 14% (16%) of gross output. Yet, these shares are surely not negligible, especially when looking at employment shares. In addition, Berlingieri et al. (2018b) and Berlingieri et al. (2018a) show that wages are increasing with productivity in both manufacturing and services: wages in the bottom decile of the productivity distribution are roughly half of those of the median productive firm. Given the large share of employment that laggards represent, this has very important policy implications for inclusiveness, not only in terms of productivity growth but also of employment and wages.

Figure 6. Share of gross output, value added and employment by LP group



Note: The figure plots the average share of gross output (GO), value added (VA) and employment (L) in each group of the productivity distribution. In particular, the LP distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE.

When focusing only on the bottom 10% of the LP (MFP) distribution, the contribution of laggards to aggregate productivity is small. The bottom 10% accounts for around 5% (7%) of total employment, 1% (4%) of value added, and 2% (5%) of gross output. Therefore, when considering only the very left tail of the productivity distribution, at a first look laggards might appear virtually insignificant. Given the small share of resources used by low productivity firms, one might be tempted to think that their poor performance matters very little not only for aggregate productivity levels, but also for aggregate productivity growth.

A first appraisal of the role of laggards on economic performance is given by their contribution to the level of aggregate productivity within industries. Therefore, an exercise to calculate the contribution of laggards to aggregate labour productivity is performed (see Box 2 for a detailed explanation). According to this exercise, the 10% least productive firms contribute on average to less than 1% of the total productivity in the 2-digit industry, whereas the bottom 40% contributes to about 10%.[28]

The small contribution of laggards to aggregate productivity is not surprising, and is the result of a combination of their relatively small (although certainly not negligible) share of employment and their low productivity. However, this does not allow to properly identify the drag to aggregate productivity growth that these firms represent or, conversely, the gains that could be achieved should these firms raise their productivity to the level of the median firms. In order to gauge that, a counter-factual exercise

(see the details in Box 2) is performed to measure the potential productivity gains resulting from a hypothetical situation where the (weighted) average productivity in each productivity group is equalised to the level of the (weighted) average productivity in the central part of the distribution (the p(40-60) group). As previously emphasised, the laggards group comprises entering firms with a potential for growth or experimenting firms rapidly exiting the market due to firm dynamics, but also low productivity firms that survive when they should in fact exit the market due to market selection. This counterfactual exercise therefore does not assume that the productivity of all laggards could converge to the median level. Instead, the experiment can be thought as trying to measure potential productivity gains resulting, for instance, from better selection and better allocation of resources from the worst performing firms to more productive ones, combined with an economic environment and policies favouring laggards' productivity growth, for instance by encouraging the diffusion of technology and knowledge.

Box 2 Calculating the contribution of laggards to aggregate productivity

As explained in more detail in Berlingieri et al. (2017a), the contribution of firms with different LP (i.e., in different LP groups) to the aggregate LP in the sector can be computed as follows:

$$P_{jt} = \sum_i \frac{L_{ijt}}{L_{jt}} P_{ijt} = \sum_q \frac{L_{qjt}}{L_{jt}} \sum_{i \in q} \frac{L_{ijt}}{L_{qjt}} P_{it} = \sum_q \frac{L_{qjt}}{L_{jt}} \overline{P}_{qjt}, \quad (4)$$

where $\overline{P}_{qjt}$ is the weighted average LP in the LP group q of 2-digit industry j, and $\frac{L_{qjt}}{L_{jt}}$ is the labour share of LP group q with respect to sector j. The contribution of a specific LP group q is given by $\frac{L_{qjt}}{L_{jt}} \overline{P}_{qjt}$: it is jointly determined by its employment share in the industry total employment, and by the index of aggregate productivity (employment weighted average of firm LP) in this group. In order to evaluate the contribution of each group to the aggregate productivity, the contribution computed from Equation (4) is then normalized by the level of LP in the industry. The normalized contribution is hence given by $(\frac{L_{qjt}}{L_{jt}} \overline{P}_{qjt})/P_{jt}$.

Moreover, the potential gain from raising LP of laggards to the level of the median firms is computed for each LP group, 2-digit industry, and year in the following way:

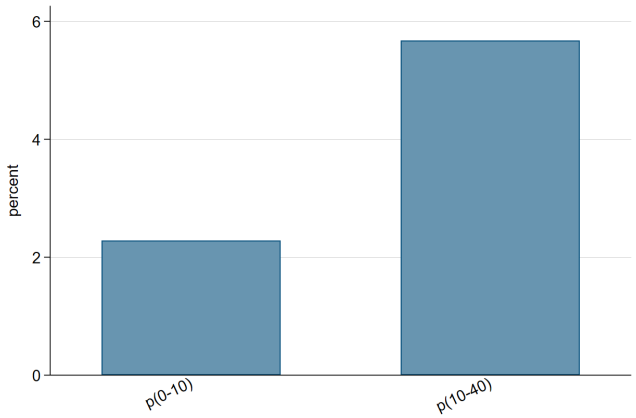
$$gains_{qjt} = \frac{L_{qjt}}{L_{jt}} \times (\overline{P}_{q_{median}jt} - \overline{P}_{qjt}) \quad (5)$$

where $\overline{P}_{q_{median}jt}$ is the (weighted) average LP for firms belonging to the median LP group, i.e., the 4^{th}-6^{th} decile of the LP distribution in industry j. The potential gain is then normalised by the level of LP in this industry in the same year:

$$gains^N_{qjt} = \frac{gains_{qjt}}{\overline{P}_{jt}}.100 \quad (6)$$

Figure 7 plots the potential gains from raising productivity in p(0-10) and p(10-40) to the level of productivity in the central part of the distribution (p(40-60)). The potential gains deriving from pushing the laggards to the median level is remarkable. On average, aggregate LP would increase by 2% in each industry by raising the productivity of the bottom p(0-10); for p(10-40) the increase would be around 6%. These benefits would obviously require significant improvements in productivity: for the bottom 10%, this would require a five-fold improvement in productivity performance, whereas for firms belonging to p(40-60) this would require an increase in productivity of almost 60%. The exercise, however, is aimed at showing that, despite their relatively low weight, laggard firms could potentially play an important role

Figure 7. Average gains from raising labour productivity to the median level



Note: The figure plots average gains hypotetically achievable by raising labour productivity in each group of bottom of the productivity distribution to the median level. The productivity distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. The bars of this figure are computed in the following way: first gains are aggregated across industries within country and productivity groups using employment shares of the industry in the economy. Subsequently, a simple average is computed across years within each country-productivity group. Finally, the median is computed over countries, separately for p(0-10) and p(10-40).

in increasing aggregate productivity. Therefore, policies targeting productivity improvements for the least productive firms may significantly increase aggregate productivity.

To sum up, the report has so far highlighted that, at the bottom of the productivity distribution: i) productivity is markedly lower than in the rest of the economy; ii) firms tend to be younger and smaller than average; iii) on average firms grow faster than in the rest of the distribution; iv) a non-negligible share of workers (around 30%) is employed in laggard firms; v) significant gains could be achieved by raising their productivity to the median level; vi) the environment is particularly heterogeneous, with a higher share of entrants and exiting firms, and is characterised by stronger reallocation than elsewhere in the productivity distribution. All these elements together suggest that when looking at laggards it is of the utmost importance to go beyond a static analysis of their characteristics and performance, and adopt instead a more dynamic perspective. As stated before, indeed, the "group" of laggards is also populated by young firms at their first stage of development, operating below their efficiency levels, but more responsive to productivity shocks (Decker et al., 2018), growing faster than the average and, therefore, with possibly high potential to become the future productivity frontier.

At the same time, it has been widely shown that the productivity divergence between top and laggard firms is rising, both globally (Andrews et al., 2016) and within countries and industries (Berlingieri et al., 2017b). This phenomenon could be rationalised by technological divergence due to a lack of diffusion stemming from increasing costs for laggard firms to adapt to the new digital/knowledge intensive economy (see Brynjolfsson et al., 2017), or from rising barriers in adopting technology due to a lack of absorptive capacity (see OECD, 2017 and Figure C.9 in the Appendix).

Overall, the report has already shown that the presence of firms lagging behind in terms of productivity is not necessarily the sign that an economy performs badly, since it also reflects firm dynamics through entry and exit. What is at stake, however, is the capacity of laggard firms to escape the low productivity group by either exiting the market or improving their productivity to catch up with the rest of the economy. Therefore, the rest of the report focuses more closely on the catch-up of laggards

and investigates the hypothesis that the transition to a digital and knowledge economy is associated with barriers to diffusion. The next section: i) provides an empirical framework to analyse the catch-up of laggard firms, and to quantify the role of different factors for catch-up; ii) presents the measures of digital and knowledge intensity used in the analysis.

4. The determinants of diffusion: an empirical framework

Section 3 has highlighted the correlation between the average productivity of firms and their productivity growth. On average, the further the firm is from the frontier in terms of productivity, the faster its future growth. Hence, this section: i) provides an empirical framework to quantify the catch-up effect, as well as the role of different factors affecting it; ii) briefly describes the measures of digital and knowledge intensity used in the analysis.

4.1. Empirical framework

The "catch-up effect" has been widely documented in the literature (e.g., Griffith et al., 2004 and Bartelsman et al., 2008). Empirical studies have confirmed the existence of a catch-up effect both at the firm level (Griffith et al., 2009, Bartelsman et al., 2008, Andrews et al., 2015, Andrews et al., 2016) and at the industry level (Nicoletti and Scarpetta, 2003, Saia et al., 2015). This report complements the existing evidence by exploiting the richness of the MultiProd database, which combines the benefits of a micro-aggregated approach with the generality of a cross-country framework, to test the existence of the catch-up of laggards to the national frontier in the same industry and explore possible heterogeneity in the strength of the effect.

The starting point of the econometric analysis is the following convergence equation (derived from a theoretical framework in Appendix A):

$$\Delta \ln A_{cjq,t} = \lambda \Delta \ln A_{cjF,t} + \beta_1 \ln \left(\frac{A_F}{A_q}\right)_{cj,t-1} + \beta_2 \ln \left(\frac{A_F}{A_q}\right)_{cj,t-1} \times X_{cj,t-1} + \rho X_{cj,t-1} + u_{cjq,t} \quad (7)$$

where $A_{cjq,t}$ is labour or multi-factor productivity in country c, industry j, productivity performance group q, and time t (and $\Delta \ln A_{cjq,t}$ is productivity growth). $A_{cjF,t}$ is productivity at the national frontier in the same country, industry, year. $X_{cj,t-1}$ denote firm or industry characteristics that affect productivity growth (either directly or through the speed of catch-up), and $u_{cjq,t}$ is a stochastic error term.

Equation (7) is the starting point of the econometric analysis performed in the report. However, productivity growth can be affected by macroeconomic shocks at the country level and by industry characteristics, possibly correlated with the explanatory variables. In order to control for them, the error

term in (7) is allowed to include country-year and industry fixed effects:

$$u_{cjq,t} = \delta_{ct} + \tau_j + \varepsilon_{cjq,t}$$

Therefore, guided by equation (7) the strength of the catch-up effect and its determinants can be assessed by estimating the following equation:

$$\Delta P_{cjq,t} = \alpha + \beta_1 gap_{cjq,t-1} + \beta_2 (gap_{cjq,t-1} \times X_{cj,t-1}) + \rho X_{cj,t-1} + \lambda \Delta P^F_{cjq,t} + \delta_{ct} + \tau_j + \varepsilon_{cjq,t} \quad (8)$$

The report estimates this equation for laggard firms, i.e., the "left tail" of the productivity distribution (productivity groups p(0-10) and p(10-40)). $P_{cjq,t}$ denotes the measured average (log) productivity (LP or MFP) in country c, industry j, productivity performance group q (productivity groups (p(0-10) and p(10-40)) and year t.[29] $\Delta P_{cjq,t}$ is then the annual (log) productivity growth of firms belonging to the bottom 40% of the productivity distribution at time $t-1$, whereas $\Delta P^F_{cjq,t}$ is the annual (log) productivity growth of firms at the national frontier in t, defined as the top 10% of the productivity distribution in each country-2 digit industry-year. Moreover, $gap_{cjq,t-1}$ is the productivity gap at time $t-1$, modelled as the distance between (log) productivity in each country-industry-productivity group-year in the bottom 40% of the productivity distribution and (log) productivity in the corresponding country-industry-year in the top 10%. Finally, $X_{cj(q),t-1}$ denotes main variables of interest, reflecting structural factors possibly affecting the strength of the catch-up effect.[30] Standard errors are clustered at the country-industry level, in order to account for correlation of the residuals in an unconstrained way within country-industry.[31]

The main parameters of interest are the estimates of β_1 and β_2. The former captures the average speed of convergence of laggard firms, whereas the latter captures whether each factor X considered hinders or fosters laggards' technological catch-up. The variable $\Delta P^F_{cjq,t}$ controls for the potential growth of the industry, i.e., the fact that firms belonging to different industries might have different potential growth rates.

It is worth noting that in this report the frontier for each industry is defined at the national level, rather than at the global level. Previous studies have shown that productivity growth of laggard firms within a country is more strongly related to the productivity of the most advanced domestic firms rather than to those (mainly foreign) firms at the global frontier (Bartelsman et al., 2008, Iacovone and Crespi, 2010). Laggard firms may indeed lack the absorptive and investment capacity to converge to the global frontier but may still learn from the national frontier and catch-up. Given the focus on laggards, the national frontier seems therefore the most relevant reference point to look at knowledge and technology diffusion and its determinants.[32]

This report aims at providing evidence of whether the digital transformation and the transition to a knowledge economy may contribute to a decline in the speed of catch-up by raising additional barriers. To this aim, the paper investigates differences in the speed of catch-up across industries and in particular tests whether digital and knowledge-intensive industries display lower rates of catch-up. The next sub-section describes the measures of digital and knowledge intensity used in this paper.

4.2. Measuring digital and knowledge intensity

This report uses six indicators of digital intensity capturing different facets of digitalisation, and two indicators of knowledge (skill) intensity. All of them, described below, vary at the 2-digit industry level, and aim at capturing industry-specific structural characteristics in terms of their exposure to digital technology on one hand, and their need for a highly-skilled/highly-specialised labour force on the other.

Measuring digital intensity is challenging for two main reasons: i) it is a multi-facet phenomenon, and ii) there are significant limitations to the availability of data. In order to circumvent these issues, Calvino et al. (2018) have proposed a classification that benchmarks industries by their degree of digital intensity. It looks at digitalisation in its various manifestations, and in particular its technological components (tangible and intangible ICT investment, purchases of intermediate ICT goods and services, robots), the human capital it requires to embed technology in production (ICT specialists intensity and ICT task intensity), and the way it changes the interface of firms with the output market (online sales). Industries are thus ranked by their intensity in these dimensions. In addition, a single value summarising all the dimensions considered is attributed to each industry, and this permits the creation of a global taxonomy that encompasses the different aspects of digitalisation.

The present report therefore uses a number of indicators in order to capture different facets of digitalisation. Firstly, it makes use of the above-mentioned global taxonomy (Calvino et al., 2018). Based on this global index, industries are divided into digital and non-digital industries.[33] Moreover, a number of indicators underlying the global index have been taken into account separately, specifically those related to the two dimensions of digitalisation of main interest for the report, i.e., the technological dimension and the human capital one.[34]

The technological dimension of the digital transformation is explored with the above mentioned global index and four of its underlying indicators: 1) investment intensity in ICT equipment; 2) investment intensity in software and databases; 3) ICT goods as intermediate inputs; 4) ICT services as intermediate inputs. The measures of investment intensity in ICT equipments (computer hardware and telecommunication equipment) (measure 1), and software and databases (measure 2) take into account investments in tangible and intangible ICT capital respectively. The first is based on investment in ICT equipment as a percentage of total gross fixed capital formation (GFCF). The second one is based on purchases of software and databases also as percentage of GFCF. These measures of ICT investment intensity, however, may not entirely account for the use of digital technologies in production, given that accounting rules recommend the capitalisation of expenditure if a purchase has a “useful life of more than one year” (Calvino et al., 2018). This excludes some goods or services that are used for a shorter duration (such as software purchased with one year licenses, IT consulting, data processing) and are therefore not taken into account in measures of ICT investment. However, such expenses could be particularly relevant to take into consideration given that firms may choose to purchase ICT intermediates instead of investing themselves in ICT capital, in order to adjust capacities more rapidly, adapt to fast changing technologies, avoid maintenance costs and circumvent financial constraints. Therefore, these measures are complemented with measures of the use of ICT goods (measure 3) and services (measure 4) as intermediate inputs. Purchases of ICT intermediate goods and services (measures 3 and 4) are based on the OECD Inter-Country Input-Output (ICIO) database, and are both normalised by real output.[35]

The final measures used in this report are cross-country averages of the underlying data for the period 2001-2003 in each industry, i.e., they are at the industry-level and time invariant. Consequently, these indicators do not capture existing heterogeneity in the use of digital technologies across countries in the same industries, nor changes over time. Nonetheless, they are still likely to capture structural industry characteristics regarding the scope for the use of digital technologies. Using a cross-country average at the beginning of the period also attenuates concerns about endogeneity due to reverse causality. In addition, Calvino et al. (2018) show that the ICT investment intensity in 2001-2003 is largely correlated with changes in the intensity between 2001-2003 and 2013-2015. Therefore, the measure can be interpreted not only as an indicator of structural differences in digital intensity, but to some extent also as a measure of digitalisation, i.e., the change in the digital intensity over the period.

In addition, the human capital dimension of the digital transformation is explored with a measure of ICT task intensity.[36] The penetration of digital technologies is transforming occupations and the skills needed by workers to perform their job. The OECD Programme for the International Assessment of Adult Competencies (PIAAC) dataset provides information on the frequency with which surveyed individuals carry out tasks which are related to the use of ICT on the job. This occupational based measure is translated into an industry measure of ICT task intensity using the weight of different occupations in each industry (for details, see Grundke et al., 2017 and Calvino et al., 2018). It is, however, available for 2012 only. The use of this variable in the empirical framework, therefore, relies on the underlying assumption that it correctly reflects industry differences in ICT task intensity in the earlier period. This assumption seems plausible. Indeed, when looking at ICT intensity in terms of ICT investment and usage of ICT intermediates, there is a correlation between the relative digital intensity at the beginning of the period (2001-2003) and digital intensity at the end of the period (2013-2014). Therefore it can be assumed that similar correlations prevail for other dimensions of digital intensity so that the relative ICT task intensity of industries in 2012 also broadly reflects the relative ICT task intensity in the earlier period.

Secondly, the present report looks at two knowledge intensity measures, in order to test the hypothesis that knowledge intensive sectors, facing potential obstacles to diffusion, are characterised by a lower speed of catch-up. The first measure is based on industry-level skill intensity computed as the share of hours worked by high-skilled (i.e., tertiary-educated) workers.[37] In this report, the skill intensity of each industry is computed as the average over the period 1995-1999 for the United States. Despite not taking into account existing heterogeneity across countries and changes over time, using an indicator of skill intensity that varies at the industry level only and based on the US has several advantages. First, it maximises the size of the sample used for the regressions, given the availability limitations of the country-industry-time varying measure.[38] A second advantage is that it is less subject to endogeneity problems.[39] The use of a measure computed for a benchmark country is indeed a common way to ensure exogeneity (see for instance Rajan and Zingales, 1998).[40] In addition, a second measure of knowledge intensity focusing on services has been used. It divides non-financial market services into knowledge-intensive services (KIS) and less knowledge-intensive services (LKIS). This index relies on the Eurostat classification of knowledge-intensive services, which is based on the share of tertiary educated persons at the NACE Rev.2 2-digit level.[41]

5. Heterogeneity of catch-up and barriers to diffusion

This section first provides evidence confirming that the catch-up effect related to knowledge and technology diffusion is a robust – although not the only one – source of productivity growth for laggards, especially for younger firms. However, it then documents a decrease in the speed of catch-up that indicates potential barriers to diffusion. The hypothesis that the digital transformation and the transition to a knowledge economy contribute to this slowdown is then explored by investigating differences in the speed of catch-up across industries. Finally this section shows that a lower speed of catch-up in digital and knowledge intensive industries is associated with higher levels of productivity dispersion.

5.1. Diffusion: a driver of productivity growth, especially for young firms

This section first confirms the (expected) catch-up effect for the group of laggards. Studies testing the existence of a catch-up effect at the country or industry level generally test whether the average firm in a country (or country-industry) lagging behind the frontier is able to catch up. The implicit assumption is that within a country all firms in a particular industry have the same productivity. In contrast to this literature, this report focuses on firms at the bottom of the productivity distribution – the 40% least productive firms – and quantifies the positive relationship between the productivity gap and the productivity growth of laggards.

Table 3 shows the baseline results that quantify the strength of the catch-up effect (columns 1 and 2, including or excluding productivity growth of the frontier as a control), tests the potential difference between manufacturing and market services (column 3), and assesses the influence of firms' average age (column 4). In other words, in the baseline (columns 1 and 2) $X_{cj,t-1} = 0$, whereas each of the next columns report the results when controlling for a different $X_{cj(q),t-1}$, specified as title of the column.

All regressions confirm a positive relationship between the productivity gap and productivity growth of laggards, indicating the existence of convergence forces, even at the bottom of the distribution. Stated differently, a positive and significant coefficient for both LP (Table 3a) and MFP (Table 3b) gap, corresponding to estimate of β_1 in Equation 8, indicates that firms which are further behind the national frontier experience on average higher rates of productivity growth. This catch-up effect is economically very relevant.[42]

In column (3) of Table 3, the speed of catch-up is allowed to vary across different sectors of the economy by further interacting the productivity gap with a dummy variable equal to 1 for non-financial market services and 0 for manufacturing. In this setting, the coefficient associated with the gap variable (first row) measures the catch-up effect for firms in manufacturing, whereas the interaction with the dummy variable quantifies the additional effect for firms in non-financial market services. The result suggests a slower catch-up for laggards belonging to non-financial market services but, while this difference is significant at the 10% level for MFP (Table 3b), it is insignificant for LP (Table 3a).

Table 3. Productivity growth and catch-up: baseline

(a) Labour productivity

	(1) Baseline (1)	(2) Baseline (2)	(3) Service dummy	(4) Av. age
LP gap	0.1932***	0.1956***	0.2180***	0.2813***
	(0.019)	(0.019)	(0.009)	(0.024)
LP gap × X			-0.0247	-0.0104***
			(0.017)	(0.002)
Adj. R-Square	0.721	0.733	0.734	0.796
Observations	5965	5946	5946	3499
Num countries	13	13	13	7
LP growth top firms	no	yes	yes	yes
country-year sector FE	yes	yes	yes	yes

(b) Multi-factor productivity

	(1) Baseline (1)	(2) Baseline (2)	(3) Service dummy	(4) Av. age
MFP gap	0.1344***	0.1346***	0.1709***	0.2151***
	(0.020)	(0.020)	(0.011)	(0.024)
MFP gap × X			-0.0409*	-0.0078***
			(0.021)	(0.002)
Adj. R-Square	0.447	0.447	0.452	0.596
Observations	5366	5315	5315	3193
Num countries	13	13	13	7
MFP growth top firms	no	yes	yes	yes
country-year sector FE	yes	yes	yes	yes

Note: "LP (MFP) growth top firms" corresponds to LP (MFP) growth between $t-1$ and t of firms in the top decile of the LP (MFP) distribution at time *t-1*. LP (MFP) gap is computed as the difference between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Due to censoring on the firm birth year variable in some countries, regressions reported in column (4) include 7 countries only: BEL, DNK, FRA, IRL, ITA, NOR, SWE. Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Column (4) focuses instead on differences in catch-up rates for firms in different stages of their life-cycle (by interacting the productivity gap with the average age of laggards).[43] Although the age variable is available only for 7 countries out of 13, the results suggest that younger laggard firms catch up more rapidly. In line with the descriptive evidence presented previously in this report, this in turn seems to suggest that the composition of the group of laggards matters for the future of productivity. In particular, the result confirms that younger firms have a higher potential for productivity growth.

In order to corroborate the results and control for omitted factors that can affect the estimates, similar regressions with a different – more restrictive – set of fixed effects have been estimated. In Table D.9 of the Appendix all regressions include country-industry-productivity performance group and year fixed effects, in order to identify a catch-up effect from the within group variation. This controls for all time-invariant differences between country-sectors, but also different characteristics of firms across productivity performance groups within a country-sector. Our results are mostly confirmed.[44]

To sum up, the (expected) catch-up effect is confirmed also for laggard firms, suggesting that technology and knowledge diffusion is indeed a robust source of productivity growth, even at the bottom of the productivity distribution. Importantly, the report uncovers differences in the rate of

catch-up depending on firms' characteristics (age) and to a lesser extent between manufacturing and services. The higher rate of catch-up for younger firms confirms their potential contribution to productivity growth through knowledge diffusion. The suggestive evidence on differences across sectors call for further investigation of the relation between industry characteristics and the speed of catch-up. Such investigation, presented in the next sub-section, highlights both a decline in the speed of diffusion and the existence of possible barriers to diffusion potentially related to structural changes of the economy, and in particular to the digital transformation, skill-biased technological change and the transition to a knowledge economy.

5.2. Declining speed of catch-up over time

In the previous sub-section, the report has confirmed the validity of Neo-Schumpeterian growth models, which predict that firms lagging behind should grow faster by learning from the best (Aghion and Howitt, 2006; Acemoglu et al., 2006) and has shown that the effect is stronger for young firms. According to these models, productivity growth depends on two main factors: the distance to the productivity frontier, and the ability to learn from the frontier.

However, a number of studies have pointed out the fact that technological progress, while improving the scope for productivity gains, also requires overcoming potential barriers to the diffusion of technology and knowledge. The diffusion of innovation does not occur automatically, but requires a costly process of adoption, influenced by firms' capabilities and incentives to learn from the most innovative ones (see Griffith et al., 2004 for instance). In addition, the digital transformation and the transition to a knowledge economy seem to have intensified the role of capabilities and incentives (Andrews et al., 2015; Andrews et al., 2016), thus raising further obstacles to a broad diffusion of technology and knowledge. Brynjolfsson et al. (2017) highlight that it takes a considerable time to be able to sufficiently harness new technologies. This is especially true for those major new technologies that ultimately have an important effect on aggregate productivity statistics and welfare (general purpose technologies). The intuition is that the more profound and far-reaching is the potential restructuring, the longer the time lag between the initial invention of the technology and its full impact on the economy and society. This explanation implies that the promise of new technologies does not translate in aggregate productivity growth until a sufficient stock of the new technology is built and the necessary invention of complementary processes and assets occurs. Recent evidence, however, shows that the adoption of digital technologies can be hampered by the lack of incentives and capabilities (Andrews et al., 2018).

Investments in intangible assets have become more necessary to catch up with leaders and to outperform competitors. As an illustration, the transition to an economy based on ideas further increases human capital requirements, reinforcing the need for good management and training of workers. Similarly, the digitalisation of the economy strengthens the role of investments in ICT equipment and ICT intangible assets – such as software and databases – but also requires appropriate skills. More generally, skill-biased technological change relies on a stronger complementarity between technology and skilled labour, in turn reinforcing the need for complementary investments in human capital. For instance, firms benefit from investment in computers if they also invest in software, train workers to use it, and hire ICT specialists for installation and maintenance. In addition, other forms of complementarity arise. For example, investment in brand capital may allow firms to gain market share, and consequently further exploit economies of scale and benefit from network externalities. Overall, these synergies

between intangible assets are a driving force of productivity growth, but also imply that adopting new technologies and using them efficiently may require significant investments, potentially hampering the diffusion process.

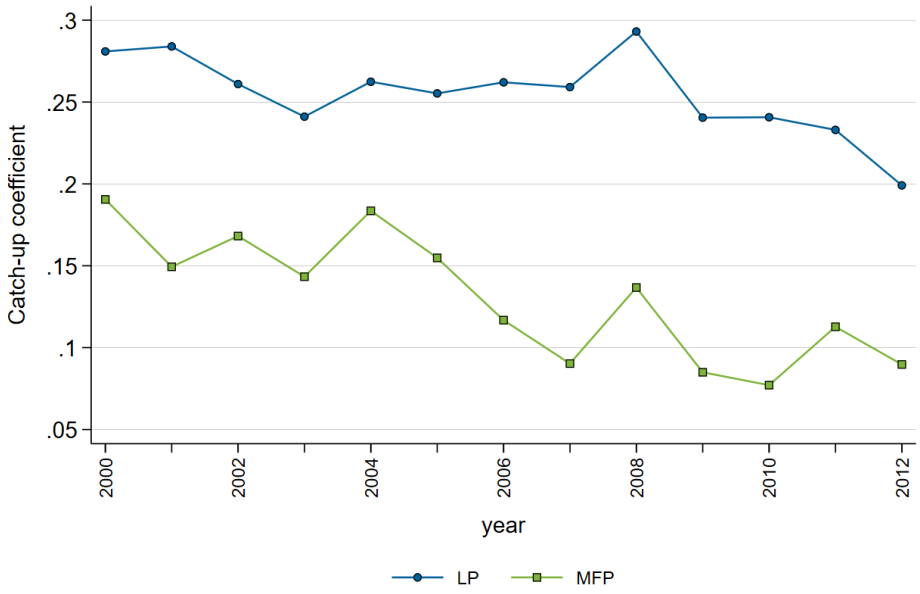
The need to finance these investments may indeed be one of the (many) potential barriers to technology adoption. Laggard firms, which are generally younger and smaller, might face greater difficulties financing investments in intangible assets, due to both the nature of intangibles per se and the existence of frictions on financial markets. Intangible capital (whether externally purchased or internally created) is indeed cursed with characteristics that might impede its financing (see Demmou et al., 2019). It is particularly subject to asymmetries of information (such as difficulties in assessing the quality of a project) making its return uncertain and risky, and therefore more costly to finance. It is also generally highly firm specific, with a low liquidation value, and therefore provides little collateral value. These characteristics are likely to reduce the borrowing capacity of financially constrained firms (Almeida and Campello, 2007). In turn, the lower availability of external financing sources to invest in intangible capital may disproportionately affect young and small firms (and hence also laggards), which are more likely to be financially constrained (Gertler and Gilchrist, 1994, Whited and Wu, 2006, Hadlock and Pierce, 2010). These obstacles to financing are potentially slowing down the adoption of new technologies and complementary investments necessary to catch up.

The existence of potential barriers to adoption (cost, capabilities, incentives) implies that the penetration of new technologies may not only be slow, but also potentially heterogeneous across groups of firms. As an illustrative example, Figures C.10 and C.11 in the Appendix show the heterogeneity in the speed of adoption for small and large firms. It displays the difference in the usage of cloud computing services (Figure C.10) and in the access to higher speed broadband – download speed at least 100 Mbit/s – (Figure C.11) between large firms (more than 250 employees) and small firms (from 10 to 49 employees), for the first and last available years in each country. Firstly, for all countries the figures highlight significant differences in the level of adoption in the two groups of firms (already highlighted in Figure C.9). Secondly, and more importantly, these figures also show a noticeable increase in the differential rate of adoption between large and small businesses over time. In most countries, the combination of these two facts suggests a faster penetration of technologies in large firms than in small ones, as well as a worsening of the diffusion mechanism over time. It shows that the digital transformation may not occur at the same pace in different groups of firms. Firms at the frontier (on average larger) may maintain a technological gap through rapid adoption of technology, while laggards may face increasing barriers to adoption. Consequently, those industries more exposed to the digital transformation may also be more likely to be characterised by a higher heterogeneity in the adoption of new technologies across firms, with possible negative consequences for the speed of catch-up.[45]

Figure 8 reinforces the concern that catch-up gets slower as the importance and exposure to digital technologies and knowledge increase. It shows a decrease in the speed of catch-up over time, for both labour and multi-factor productivity.[46] A similar decline in the speed of convergence has been documented by Andrews et al. (2016).[47] This suggests that the diffusion of technology and knowledge has slowed down over time, possibly due to the heightened importance of incentives, capabilities and complementary investments triggered by the structural transformation discussed in the report.

The decline in the knowledge diffusion intensity is also discussed by Akcigit and Ates (2019a) and Akcigit and Ates (2019b). Using an endogenous growth model of strategic interaction and innovation, the authors show that the decline in knowledge diffusion is the dominant factor behind a number of

Figure 8. Catch-up over time



Note: The figure represents the estimates for the catch-up effect over time. It plots coefficients from a regression of productivity growth on the productivity gap interacted with year dummies, including country-year and industry fixed effects. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE.

recent empirical trends, such as increasing productivity dispersion, rising market concentration, and a slowdown in business dynamism.[48] They discuss four possible drivers of the decline in knowledge diffusion. The first hypothesis is that tacit knowledge and proprietary data play a larger role in the production process. This hypothesis is also supported by additional evidence showing that mark-ups have increased more in digital-intensive sectors (Calligaris et al., 2018) and that business dynamism has also declined more rapidly in digital-intensive industries (Calvino and Criscuolo, 2019). A second possible driver is related to the regulatory framework, which may be favouring large firms, and preventing small firms from benefiting from knowledge spillovers (a hypothesis consistent with the finding of Calvino et al. (2016) that start-ups are more exposed than incumbents to the policy environment). A third possible explanation is the increasing use of off-shore production, preventing laggards from learning from the frontier through geographical proximity. Finally, Akcigit and Ates (2019b) argue that large firms may exploit patent protection to create patent thickets used for defensive purpose. The authors also document an increase in patent reallocation towards large firms and an increase in patent concentration which both support this last hypothesis.

The present report explores possible heterogeneities in the speed of catch-up to unveil the existence of barriers to diffusion consistent with the decline in knowledge diffusion and the first hypothesis mentioned above. It seems in particular consistent with increasing barriers related to the rising importance of knowledge and digital technologies. More specifically, using the empirical framework presented previously, the rest of this section tests whether laggards catch up at a lower rate in sectors more exposed to digital technologies and knowledge, as well as requiring more skilled labour. To this aim, multiple dimensions of the digital transformation are first explored, based on the taxonomy proposed by Calvino et al. (2018). Subsequently, the report investigates differences in catch-up based on heterogeneity in the knowledge intensity at the sectoral level.

5.3. Slower catch-up in digital and knowledge intensive industries

This subsection investigates differences in the speed of catch-up related to the industry characteristics described in Section 4.2. In particular, Equation (8) is estimated for laggard firms, and each measure of digital and knowledge intensity represents a different X_j in the equation. First the association between each industry characteristic and the rate of catch-up is evaluated separately. Subsequently, the role of each factor is evaluated with regressions focusing on several variables at the same time.

Table 4a and Table 4b show the results of the main regressions for labour and multi-factor productivity, respectively. Each column reports the link between the speed of productivity catch-up and the industry characteristic X_j, as specified in the title of the column. Columns (1) to (6) explore heterogeneity in catch-up across sectors featuring different degrees of digitalisation, whereas columns (7) and (8) focus on knowledge intensity. Given that in all regressions presented in Table 4 X_j varies at the industry level, the "direct effect" of the variable on productivity growth of laggards is absorbed by the industry fixed effects.[49] Thus, the results focus exclusively on differences in the speed of convergence across industries, in order to identify whether structural factors are associated with convergence or divergence forces.

Table 4. Productivity growth and catch-up of laggards: digital and knowledge intensity

(a) Labour productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
LP gap	0.2233***	0.2128***	0.2109***	0.1903***	0.1962***	0.1928***	0.2022***	0.2224***
	(0.018)	(0.014)	(0.015)	(0.019)	(0.019)	(0.018)	(0.016)	(0.020)
LP gap × X	-0.0643**	-0.0399**	-0.0322***	-0.0295***	-0.0107*	-0.0291***	-0.0346***	-0.0734**
	(0.030)	(0.016)	(0.011)	(0.011)	(0.006)	(0.010)	(0.013)	(0.030)
Adj. R-Square	0.752	0.749	0.755	0.739	0.735	0.747	0.758	0.758
Observations	5946	5946	5946	4978	5946	5946	5946	2847
Num countries	13	13	13	13	13	13	13	13
LP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

(b) Multifactor productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
MFP gap	0.1737***	0.1560***	0.1545***	0.1332***	0.1390***	0.1358***	0.1495***	0.1815***
	(0.012)	(0.013)	(0.013)	(0.020)	(0.021)	(0.018)	(0.011)	(0.016)
MFP gap × X	-0.0790***	-0.0400***	-0.0315***	-0.0336***	-0.0182***	-0.0311***	-0.0394***	-0.0938***
	(0.024)	(0.015)	(0.009)	(0.008)	(0.004)	(0.008)	(0.010)	(0.025)
Adj. R-Square	0.490	0.477	0.486	0.462	0.460	0.476	0.498	0.494
Observations	5315	5315	5315	4386	5315	5315	5315	2340
Num countries	13	13	13	13	13	13	13	13
MFP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

Note: LP (MFP) growth top firms corresponds to LP (MFP) growth between *t-1* and *t* of firms in the top decile of the LP (MFP) distribution at time *t-1*. LP (MFP) gap is computed as the difference between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). All variables *X* are standardized, except in columns (1) and (8) where *X* denotes dummy variables. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The results point in the same direction: laggards catch up at a lower rate in more digital-intensive and more knowledge-intensive industries. While a higher use of digital technologies and knowledge

may be beneficial for overall productivity growth, they seem nonetheless to push towards divergence in productivity, possibly due to barriers preventing the rapid adoption of technology by laggards and hampering the diffusion of knowledge from frontier firms.

The results hold for all facets of digitalisation described in the previous section. In column (1), industries are divided into digital and non-digital based on the global digital taxonomy.[50] This shows that firms belonging to more digital intensive sectors are catching up at a lower rate than those in the less digital ones. This effect is economically significant, as illustrated in a subsequent exercise.[51] The lower rate of catch-up in digital sectors suggests stronger barriers to diffusion of technology and knowledge in these sectors. In other words, the potential gains from digitalisation may not equally benefit all firms. These results are in line with evidence that adoption of digital technologies is heterogeneous across firms due to differences in capabilities and incentives (Andrews et al., 2018). Focusing on specific digital technologies (high-speed broadband, ERP, CRM, cloud computing), Gal et al. (2019) also find that operating in a more digital environment is associated with higher productivity growth at the firm level, but that productivity gains are larger for more productive firms.

A slower diffusion in more digital intensive industries is also uncovered when focusing on specific facets of the digital transformation. Columns (2) and (3) show that sectors characterised by more intensive investments in ICT, both tangible (Column 2) and intangible (Column 3), also display a lower rate of convergence. This may reflect heterogeneity in the extent to which firms invest in ICTs within these sectors, since laggards may lack the capability to invest. Firstly, there is a direct cost of investment that can be difficult to finance, especially for laggard firms that are more likely to be financially constrained, particularly for investment in intangible capital. Secondly, there might be an indirect cost, given that benefiting from ICT investments also requires complementary investments (in complementary technologies, human capital or organisational capital). In other words, investing in ICT capital reinforces the need to develop firm's absorptive capacity.

Another crucial aspect of digitalisation for firms is the purchase of ICT intermediate goods and services. In some cases, such purchases may be substitutes to ICT investment. For instance, DeStefano et al. (2019) show that cloud computing, "enabling a shift in the nature of ICT use, from investment in sunk capital to a pay-on-demand service" allows firms (especially young ones) to rapidly scale-up both in terms of employment and productivity. Despite the new possibilities opened by this shift, columns (4) and (5) of Table 4 indicate a lower speed of catch-up for laggards in industries where purchases of ICT goods and services as intermediate inputs are more prevalent. The negative coefficients in column (5) seems therefore in contradiction with the benefits associated with the higher accessibility of ICT services, such as cloud services, highlighted by DeStefano et al. (2019). However, additional exercises presented in the report show that a higher use of ICT intermediates does not weigh heavily on the catch-up of laggards (see Figure 9 and Figure 10) and might even increase the speed of catch-up when other aspects of digitalisation are accounted for (see later discussion of results presented in Table D.11a and Table D.11b). Together, these results may qualify the finding of DeStefano et al. (2019), by suggesting that ICT capital is a pre-requisite to benefit from ICT services, such as cloud. More generally, a broader use of ICT services also requires complementary investments in enabling infrastructures, investment in ICT capital and in human capital.

Therefore, while ICT services may contribute to a wider diffusion of ICT in the production process, especially by young and small firms, some barriers may still hamper a broad usage of such services. This is illustrated by the difference in the adoption of cloud computing between small and large firms

(Figure C.10), which shows that the use of such services remains heterogeneous across firms. Two type of barriers could explain such heterogeneity. Firstly, as mentioned above, while ICT services largely facilitate access to digital technologies, they do not eliminate completely the need for absorptive capacity and complementary investments. For instance, using cloud services requires a certain level of ICT skills and a stable and high-speed broadband connection (which may be more expensive or even not available in some geographical areas).[52] Secondly, laggards may not be able to benefit from synergies that leverage the potential of these technologies (such as using cloud computing to deal with big data obtained from large networks).

Finally, digital transformation also affects the content of jobs and changes the mix of skills that are required by firms. Approaching digitalisation from the human capital side, column (6) of Table 4 shows that laggards catch up at a lower rate in industries in which the number of ICT tasks are higher. As the need for ICT skills is increasingly widespread across a broad range of occupations, firms may face shortages in ICT skills, especially in sectors with the largest needs. Due to the cost of training workers, laggards firms may lack the capacity to update their workers' skills and promote lifelong learning processes. Furthermore, given that wages and productivity are positively related (Berlingieri et al., 2018a), laggards may face greater difficulties in attracting talented workers with the right skills.

Similarly, laggards further behind the frontier catch up at a lower speed in industries characterised by a higher share of hours worked by high-skilled workers (Column 7), suggesting again possible barriers to diffusion in these sectors. The result also holds when services are divided into a group of knowledge intensive services (KIS) and less knowledge intensive services (Column 8). The mechanisms are likely to be very similar to those underlined above. The slower catch-up in knowledge intensive industries may reflect the fact that educated workers are highly sought after by firms, putting upward pressure on their wages. More generally, laggard and young firms might find it hard to compete with more productive firms to hire precisely the workers that might be key for technological and knowledge adoption, given the complementarity with human capital and digital skills in particular (Harrigan et al., 2016). More generally, potential skill shortages disproportionately affecting laggards could be driven by the fact that skill-biased technological change raises an immediate demand for high skilled workers, whereas the supply side (through the educational and training system) takes more time to adjust.

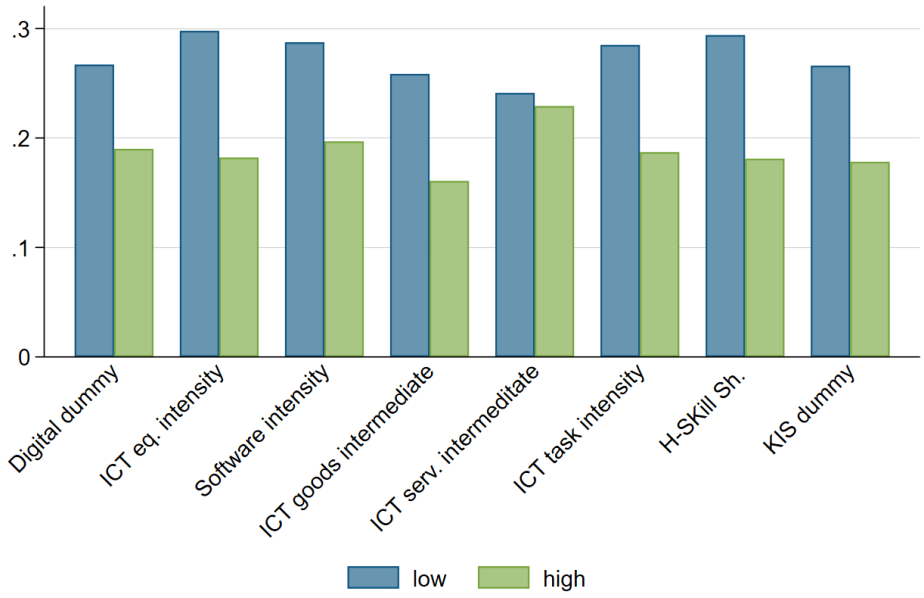
An exercise is now performed to interpret the magnitude of these coefficients, and illustrate the consequences on productivity growth of the slower catch-up in digital and skill intensive industries. To this aim, the estimated coefficients are used to compute the difference in productivity growth between firms in the p(0-10) group and those in the p(10-40) group due to the different catch-up. The estimated convergence equation implies that firms with different productivity gaps have different productivity growth (all else being equal): firms further from the frontier grow faster. As a consequence, firms at the very bottom of the productivity distribution (p(0-10) group) should improve their productivity more rapidly than firms in the p(10-40) group, as they are catching up faster.

The strength of this catch-up effect can thus be illustrated by computing the quantity $\hat{\beta}_1 \times \left(\overline{gap}_{p(0-10)} - \overline{gap}_{p(10-40)}\right)$, where $\overline{gap}_{p(0-10)}$ and $\overline{gap}_{p(10-40)}$ denote the (overall) average productivity gap in the p(0-10) and p(10-40) groups, respectively, and $\hat{\beta}_1$ is the estimated speed of diffusion. Note that this exercise uses the overall average productivity gap in order to interpret the economic implications of differences in the speed of diffusion only (i.e. differences in $\hat{\beta}$).[53] Results presented in this report, however, show that the strength of the catch-up effect depends on industry characteristics. Laggards in an industry with a high value of X_j (e.g., high skill intensity) catch up at a speed given by

$\left(\hat{\beta}_1 + \hat{\beta}_2 \times X_j^{High}\right)$, so the difference in productivity growth between firms with gap values of $\overline{gap}_{p(0-10)}$ and $\overline{gap}_{p(10-40)}$ is given by $\left(\hat{\beta}_1 + \hat{\beta}_2 \times X_j^{High}\right) \cdot \left(\overline{gap}_{p(0-10)} - \overline{gap}_{p(10-40)}\right)$. Conversely, the difference in productivity growth implied by the catch-up effect in a sector with a low value of X_j (e.g., low skill intensity) is given by $\left(\hat{\beta}_1 + \hat{\beta}_2 \times X_j^{Low}\right) \cdot \left(\overline{gap}_{p(0-10)} - \overline{gap}_{p(10-40)}\right)$.

Figure 9 and Figure 10 report for LP and MFP, respectively, the results of this exercise for the different digital and knowledge intensity indicators X_j considered in the analysis.[54] As an example, the first blue bar on the left of Figure 9 shows that in less digital intensive industries average firms in the p(0-10) group have a LP growth rate around 27 percentage points higher than average firms in the p(10-40) group (where average firms denote firms at the average value of the gap). Since catch-up is lower in more digital industries, the difference in productivity growth in these industries is a bit lower, equal to 19 percentage points (first green bar on the left). These differences are economically large for all indicators taken into account, with the exception of ICT services.

Figure 9. Estimated strength of the catch-up effect and industry characteristics, LP

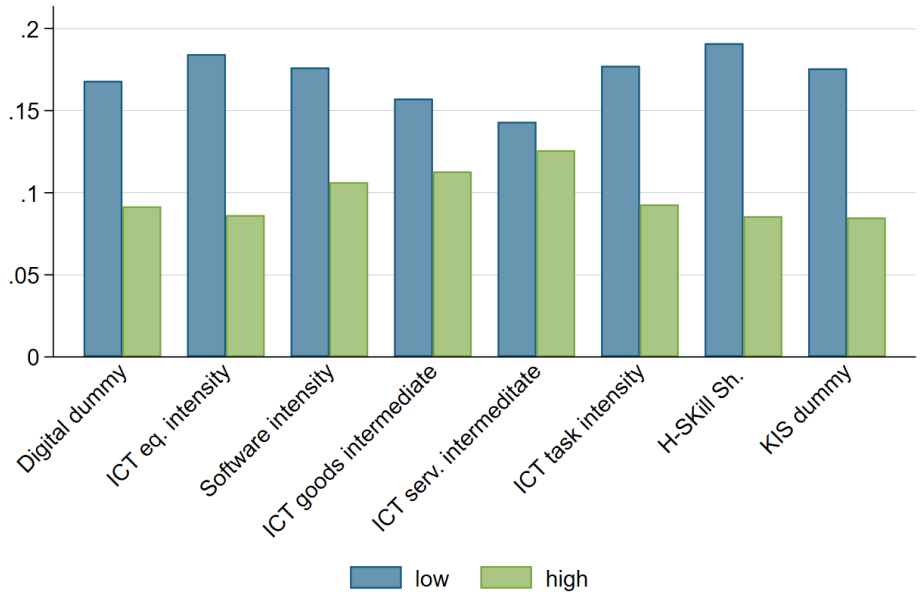


Note: The graph reports the difference in LP growth, due to the catch-up effect, between firms at the average level of LP gap in the p(0-10) group and firms at the average LP gap in the p(10-40) group, in industries with *low* vs. *high* values of the indicators considered. For dummy variables the low and high values are simply 0 and 1. For other indicators, the low and high value correspond to the 10^{th} and 90^{th} percentiles. This figure is based on the estimates presented in Table 4a.

The characteristics evaluated in Table 4 proxy for interrelated mega-trends, namely digitalisation, the rising importance of investment in intangibles and, consequently, the type and quality of jobs that are available and the skill-sets they require. Results presented in Table 4 suggest that industry-level digital and knowledge intensity, even when measured in different but complementary ways, are associated with slower catch-up of the worst performing firms. The next natural question would be which among the structural factors taken into consideration – increased digitalisation and knowledge intensity – contributes the most to the negative correlation between productivity growth and distance to the frontier.

This report, therefore, proposes a first evaluation by including in the same regression the different dimensions (interacted with the gap) analysed before. This exercise should be considered with caution given the limitations imposed by the use of time and country invariant industry characteristics and,

Figure 10. Estimated strength of the catch-up effect and industry characteristics, MFP



Note: The graph reports the difference in MFP growth, due to the catch-up effect, between firms at the average level of MFP gap in the p(0-10) group and firms at the average LP gap in the p(10-40) group, in industries with *low* vs. *high* values of the indicators considered. For dummy variables the low and high values are simply 0 and 1. For other indicators, the low and high value correspond to the 10^{th} and 90^{th} percentiles. This figure is based on the estimates presented in Table 4b.

consequently, their limited variation.[55] Moreover, not all variables can be included at the same time, given the possible collinearity induced by the high correlation among some of these dimensions (see Figure C.12 in the Appendix). To limit the risk of obtaining biased estimates due to collinearity, the exercise tests only possible relevant combinations of these determinants to give a preliminary and rough evaluation of the role of different facets of the mega-trends.

Table D.11a and Table D.11b present the results of this preliminary analysis for, respectively, LP and MFP. The first column displays the results aiming at evaluating the simultaneous role in catch-up of two types of ICT investments: tangible investments (ICT equipment) and intangible investments (software and databases). The two types of investments display a relatively high correlation, reflecting their complementarity.[56] However, when both measures are interacted with the productivity gap, only the interaction with intangible ICT investment is negative and significant, for both LP and MFP. This result suggests that investment in software and databases, given also its rising importance, may be a more prominent obstacle to the catch-up of laggards than investment in ICT equipment. Columns (2) to (4) focus more specifically on the role of ICT services as intermediate inputs when also including investment in both tangible (Column 2) and intangible (Column 3) ICT investment, and ICT skill intensity (column 4). The columns show that, conditional on the level of investment, firms in industries with a higher use of ICT services as intermediate inputs do not significantly catch up at a lower speed. For LP, a higher use of ICT services as intermediate inputs seems even to allow a faster catch-up of laggards. The latter result, that would need further confirmation, is consistent with findings of DeStefano et al. (2019). Given the importance of investment in ICT intangibles, in column (5) its role for catch-up is evaluated jointly with that of skill intensity. For LP, both interaction terms remain negative but become insignificant. However, a F-test suggests that they are jointly significant.[57] This might suggest that both dimensions are relevant for catch-up, but difficult to disentangle. Results for MFP, instead, point to the importance of skills: the

coefficient in this case is still negative and significant. Finally, column (6) evaluates simultaneously the role of the three dimensions identified as potentially most relevant.[58] Results are ambiguous, depending on whether LP or MFP is considered. However, they confirm the potential barriers in industries with higher intensity in intangible investments and higher skill intensity, and the fact that they are potentially interrelated.

To sum up, the results presented in this section show that in industries characterised by a high level of digitalisation and knowledge intensity, laggard firms face higher obstacles to growth, and therefore catch up at a lower speed. The robustness of these findings is also evaluated in Appendix B.[59] Taken as whole, these findings suggest that digitalisation and the transition to an economy based on ideas, although potentially beneficial for overall growth, may not equally benefit all firms. This in turn suggests the existence of barriers to technology and knowledge diffusion raised by these recent mega-trends. Laggards, not having the necessary absorptive capacity to learn from the frontier, struggle more to catch up in industries where digitalisation and knowledge matter the most. These barriers to catch-up may have important implications for macroeconomic performance and inequalities, given that slower catch-up is associated with higher productivity dispersion. The relationship between speed of catch-up and productivity dispersion is explored in the next sub-section.

5.4. Implication for productivity dispersion

Results presented in this report confirm the existence of catch-up among firms at the bottom of the productivity distribution, in line with the descriptive analysis highlighting the growth potential of laggards. This catch-up can be seen as a force pushing towards convergence of firms' productivity. However, recent contributions have documented an increase in dispersion between the global frontier and the rest (Andrews et al., 2015, Andrews et al., 2016), as well as between the national frontier and the rest (Berlingieri et al., 2017b). Although these two strands of literature are apparently contradictory, catch-up to the frontier is in fact consistent with persistent productivity dispersion. The existence of barriers to diffusion due to the transition to a digital and knowledge based economy is a possible culprit of this divergence (Andrews et al., 2016).

The catch-up effect is a driver of convergence. As a consequence, the lower speed of catch-up over time uncovered in the previous section can be easily linked to higher productivity dispersion. This relationship has been discussed by Griffith et al. (2000) and Griffith et al. (2009) in a setting closely related to the one used in this report. The catch-up equation, indeed, implies that the long run equilibrium level of productivity dispersion is negatively correlated to the speed of catch-up. Stated differently, a lower speed of catch-up induces a higher level of productivity dispersion, reflecting the slower diffusion of innovation. Hence, the contemporaneous existence of catch-up and divergence in productivity is justified by an equilibrium outcome reflecting a tension between an increased variation in firms' innovative capabilities – which tends to increase dispersion – and productivity catch-up – which tends to reduce dispersion.

Therefore, this report evaluates the link between levels of productivity dispersion and the sectoral characteristics used in previous regressions. More formally, the prediction of a positive correlation is tested with a regression of a rather standard measure of dispersion, the 90-10 ratio, on relevant indicators of digital and knowledge intensity at the industry level, using country-year fixed effects. The

following equation is estimated:

$$\log\left(\frac{P_{90}}{P_{10}}\right)_{cj,t} = \alpha + X_j + \delta_{ct} + u_{cj,t}. \tag{9}$$

where $\log(P_{90}/P_{10})_{cj,t}$, the measure of productivity dispersion, is the (log of the) ratio between the 90th and 10th percentiles of the productivity distribution (LP or MFP); X_j are sectoral measures of digital and knowledge intensity, and refer to the same structural characteristics as in Table 4; and δ_{ct} denote country-year fixed effects, which control for country-specific macro trends. Thus, this regression exploits industry-level differences within country-year pairs. This is in line with the focus on the link between the speed of catch-up and the long-term equilibrium *level* of productivity dispersion.[60]

Estimates reported in Table 5 for LP dispersion (and Table D.14 in the Appendix for MFP) all confirm a positive and significant correlation between dispersion in productivity and measures of digital and knowledge intensity. These findings show that the potential slowdown of knowledge diffusion discussed throughout this report, by reducing the speed of catch-up of the least productive firms, may contribute to increased dispersion. This echoes the finding of Faggio et al. (2010) for the United Kingdom, showing that changes in productivity dispersion within industries are positively related to changes in the use of ICT services.

Table 5. LP dispersion and digital and knowledge intensity

	(1) LP disp 90-10	(2) LP disp 90-10	(3) LP disp 90-10	(4) LP disp 90-10	(5) LP disp 90-10	(6) LP disp 90-10	(7) LP disp 90-10	(8) LP disp 90-10
Digital	0.2887***							
	(0.068)							
ICT eq. int.		0.2586***						
		(0.037)						
software int.			0.1484***					
			(0.034)					
purch. ICT goods				0.1694***				
				(0.050)				
purch. ICT serv.					0.0870***			
					(0.027)			
ICT task content						0.1337***		
						(0.035)		
H-Skill Sh.							0.1723***	
							(0.036)	
KIS								0.2746***
								(0.088)
Constant	1.7892***	1.8151***	1.8457***	1.9272***	1.8752***	1.9242***	1.9122***	1.8715***
	(0.033)	(0.024)	(0.026)	(0.033)	(0.030)	(0.031)	(0.031)	(0.032)
Adj. R-Square	0.756	0.809	0.772	0.724	0.709	0.749	0.803	0.796
Observations	3651	3651	3651	2987	3651	3651	3651	1654
Num countries	13	13	13	13	13	13	13	13
country-year FE	yes	yes	yes	yes	yes	yes	yes	yes

Note: "LP disp 90-10" is a measure of productivity dispersion computed as the difference between the 90^{th} and 10^{th} percentile of the log productivity distribution. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The link between dispersion and the transformation of the economy can be better understood by coming back to the determinants of dispersion, reviewed by Syverson (2011). Differences in firm productivity can be caused by differences regarding: the technology and the stock of knowledge (in

particular ICT and R&D); the quality of inputs (capital and labour); the organisation of production; the managerial quality; product innovation (allowing firms to set higher prices). While digitalisation and skill-biased technological changes are broadly affecting all of them, firms have different capabilities and incentives to learn from the frontier and, as a consequence, to quickly adjust to the recent transformations. This, in turn, calls for an analysis of the economic environment and policies that can influence firms' capabilities and incentives to harness the productivity potential arising from technological progress. This will be the object of the next section.

6. Environments and policies affecting catch-up

Section 5 has shown that higher skill requirements and digital intensity are associated with a lower speed of productivity catch-up for laggards, pointing to barriers to technology adoption and knowledge diffusion. Policy intervention has a potential instrumental role in reducing these barriers to foster diffusion, and consequentially increasing productivity growth and reducing firm inequality. Potential significant barriers to adoption – hindering a wide diffusion of the benefits associated to technological progress and slowing down the productivity growth of laggards – include changing skill needs in the economy and, thus, skill shortages in high-skilled jobs, costly complementary investments to technology, and lack of absorptive capacity.

In order to guide the policy response to the widening productivity gap, this report aims at uncovering areas that can be targeted by policy makers to favour an increased speed of diffusion. An exhaustive analysis of the policy levers is beyond the scope of this report. However this section provides evidence that enhancing skills of workers, supporting investment by monitoring financial conditions, and developing laggards' absorptive capacities through innovation policies might be relevant policy objectives.

6.1. Enriched empirical framework for policies

The report investigates whether certain economic environments and policies have the potential to influence the speed of catch-up, in particular in industries where the aforementioned barriers to diffusion – but also the potential for productivity gains – are stronger. This analysis is conducted by enriching Equation (8) as follow:

$$\begin{aligned} \Delta P_{cjq,t} &= \alpha + \beta_1 gap_{cjq,t-1} + \beta_2 (gap_{cjq,t-1} \times X_j) + \beta_3 (gap_{cjq,t-1} \times Pol_{c,t-1}) + \beta_4 (gap_{cjq,t-1} \times Pol_{c,t-1} \times X_j) + \\ &+ \beta_5 (Pol_{c,t-1} \times X_j) + \gamma (gap_{cjq,t-1} \times GDP/cap_{c,t-1}) + \lambda \Delta P^F_{cjq,t} + \delta_{ct} + \tau_j + \varepsilon_{cjq,t}, \end{aligned} \tag{10}$$

where, as previously, X_j denotes industry-level digital and knowledge intensity indicators, capturing the extent to which these industries are exposed to the mega-trends of particular interest for this analysis, namely the digitalisation of the economy, skilled-biased technological change, and the transition to a knowledge economy. $Pol_{c,t-1}$ denotes country level (time varying) policy objectives or policy instruments.[61] $gap_{cjq,t-1}$ still denotes the (labour or multi-factor) productivity gap between laggards and the national frontier, while δ_{ct} and τ_j are country-year and industry fixed effects controlling, respectively, for country-specific trends and industry characteristics. For ease of interpretation, both $Pol_{c,t-1}$ and X_j (when not a dummy variable) are standardized. Equation (10) also includes the gap interacted with GDP per-capita in a given country, in order to control for the fact that the possibility of having certain policies might be correlated with the level of development of a country. Standard errors are clustered at the country-industry level.

For this analysis, the coefficients of main interest are β_3 and β_4. β_3 measures the effect[62] of the policy on the speed of catch-up when $X_j = 0$, i.e., for the average level of the digital and knowledge intensity indicators (or, when X_j is the binary digital intensity indicator, when the dummy variable is equal to 0). β_4 accounts for the additional effect of the policy on catch-up for high levels (one standard deviation above the mean) of the digital and knowledge intensity indicators (or when the dummy is equal to one, if X_j is the digital dummy). Therefore, the policy is correlated to higher speed of catch-up for an average industry when $\beta_3 > 0$, and the effect is stronger for skill-intensive and digital intensive industries when $\beta_4 > 0$. It is worth noting that the coefficient β_2 is now interpreted as the effect of the digital and knowledge intensity indicators on the speed of catch-up at the average level of the policy.[63] When $\beta_4 \neq 0$, the effect of structural characteristics on catch-up depends on the economic environment prevailing in the country (e.g the level of under-qualification) and on relevant policies (e.g., training expenditures). In other words, if $\beta_4 \neq 0$, the negative effect on catch-up of industry characteristics (X_j) such as digital and skill intensity varies across countries depending on policies. This in turn implies that there is scope for policy makers to tackle the lack of diffusion arising from the transformation of the economy. It should also be noted that this specification is designed to investigate the potential for policies to raise productivity through increased knowledge diffusion in industries facing specific barriers, not the overall effect of such policies on the productivity of laggards.[64] Estimates of Equation (10) are presented for two industry characteristics (X) only, for brevity. In general, the dummy variable for digital industries and the measure of skill intensity are used to capture broad industry characteristics, except when focusing on other particular dimensions is more relevant.[65]

In the rest of this section, three areas of policy intervention aimed at increasing firms' absorptive capacity are successively examined: skills, finance, and R&D support.

6.1.1 Skills policies

First, the analysis focuses on policy objectives and instruments related to skills and training. The effect of the allocation of human resources is investigated first, using the proportion of workers whose educational attainment level is well matched to the level required in their job.[66] This indicator is made available at the country-year level in the OECD World Indicators of Skills for Employment (WISE) database and captures how well skills obtained through education and training correspond to the skills required in the labour market. Columns (1) and (2) of Table D.15a and Table D.15b (for LP and MFP, respectively) quantify the effect of skill matching on catch-up, also focusing on the differentiated effect for digital and skill intensive

industries. The results show that a good match between skills demand and supply is associated with a higher speed of catch-up, and there is evidence that this positive association is stronger in digital and skill intensive industries.[67]

The report then focuses on the share of workers who are under-qualified, measured as the proportion of workers whose educational attainment level is lower than the level required in their job. This particular dimension of skill mismatch, hence, focuses on skills shortage. Columns (3) and (4) of Table D.15a highlight that a lack of appropriate skills (as measured by educational attainment) in the labour force reduces the speed of catch-up and might contribute to the widening productivity gap, possibly reflecting the fact that low productivity firms may struggle in the competition for talent. This negative association between skill mismatch and the strength of the catch-up effect is particularly strong in digital and skill intensive industries. This result corroborates the intuition that changing skills requirements associated with the digitalisation of the economy and the growing importance of knowledge in the production of good and services erect barriers to diffusion when such skills are in short supply. This result also echoes the finding of Gal et al. (2019) that skills shortages reduce the productivity gains associated with digitalisation.

The previously mentioned results suggest that policies addressing skill mismatches through a better allocation of workers and an increased supply of appropriate skills could thus alleviate obstacles to diffusion. Columns (5) to (8) of Tables D.15a and D.15b investigate this, focusing on the effect of training of employed adults, as well as the effect of targeted training provided in the context of active labour market policies (ALMP). The first variable proxies for lifelong training. It refers to the proportion of working adults participating in education and training, and is based on data from the WISE database, sourced from Labour Force Surveys. The second measure uses data from the OECD database on Labour Market Programmes and refers to "active" training expenditures (relative to GDP).[68] Focusing on LP, there is evidence that both lifelong training and education support catch-up, but without a significant difference in digital and skill intensive industries. On the contrary results for both LP and MFP (Columns 7 and 8) point to a positive relation between training expenditures (from ALMP) and the speed of catch-up, particularly for digital and skill intensive sectors.

The stronger association (in particular in digital and skill intensive industries) between the speed of diffusion and higher spending on adult training in the context of ALMP rather than training of working adults could reflect the need for targeted training. Results presented in this paper, indeed, confirm that under-qualification of the workforce is hampering the process of diffusion. Higher participation of working adults in training allows adapting their skills to continuously changing skill requirements. However, there is evidence that low-skilled workers are less likely to participate in on-the-job training than other workers (Nedelkoska and Quintini, 2018). On the contrary, training targeted to the unemployed or closely-related groups (e.g., people who are inactive but would like to work, and employed people who are at known risk of involuntary job loss) might better contribute to reduce skill mismatch and might disproportionately benefit low-skilled workers. Policies aiming at enrolling low-skilled workers in training and policies specifically designed to improve their literacy and numeracy skills (see Windisch, 2015 for a survey of such policies) might contribute to lifting barriers to diffusion. In addition, other instruments are available to policy makers to reduce the incidence of skill mismatch. For example, McGowan and Andrews (2015) find that framework conditions, such as well-designed product and labour markets and bankruptcy laws that do not overly penalise business failures, are associated with lower skill mismatches, possibly because of lowering hiring and firing costs and the facilitation of smooth transitions across jobs

and, thus, better reallocation of resources across firms. The digital transformation not only changes the bundle of skills that is required, but also changes more broadly the relative demand for occupations, with some occupations becoming more prevalent and in high demand while other decline. This requires training and education policies that may be costly, reinforcing the need to define possible and acceptable transitions towards other occupations, while minimising the cost of such policies (Andrieu et al., 2019, Bechichi et al., 2019).

6.1.2 Financing policies

A second type of barrier to adoption and diffusion might be related to financing investments in both tangible and intangible ICT and in advanced technologies, as well as other complementary investments. Financial market imperfections might indeed induce a wedge in the financing capacity of different group of firms, to the detriment of laggards. A rich literature highlights that small firms are more likely to be financially constrained (Gertler and Gilchrist, 1994, Whited and Wu, 2006, Hadlock and Pierce, 2010). Given that SMEs are more represented in the group of laggard firms, barriers to their access to finance might slow the costly process of adoption among SMEs and laggards more broadly. To test whether improvement in access to finance for SMEs is a relevant policy lever, the report focuses on the link between the speed of catch-up and two relevant proxies: (i) the interest rate spread between large and small firms, and (ii) the share of SMEs' outstanding loans in total outstanding business loans. The first measure provides an indicator of differences in the cost of finance for large firms and SMEs, whereas the second one can be interpreted as an indicator of the availability of lending to SMEs.

Results are presented in Table D.16a and Table D.16b for LP and MFP, respectively. The focus is on sectors with higher ICT investment, given that tighter financial conditions are more likely to affect industries with higher needs for external finance that could be induced by the higher investment intensity. Columns (1) and (2) suggest that less favourable financing conditions for SMEs compared to large firms, revealed by higher interest rate spread, are associated with a lower speed of catch-up only in sectors that requires higher investment in ICT equipment and in software and databases. Columns (3) and (4) show that diffusion is faster in countries where a larger share of lending is directed towards SMEs, and more so in industries where investments in digital technologies are more prevalent. These results suggest that ensuring functioning financial markets may help laggards undertake profitable and productivity enhancing investments in digital technologies, with beneficial consequences for firm equality. However, these results should not be used to merely advocate for increasing lending to laggards, given that financial market imperfections may lead to misallocation of credit favouring the emergence of zombie firms. While support to laggards' access to finance can be an efficient lever to address the increasing productivity gap, such support should reach profitable firms and laggards with a potential for growth, and should be complemented by good structural policies such as efficient insolvency regimes (Acemoglu et al., 2013; Adalet McGowan et al., 2017).

6.1.3 Innovation policies

A third policy area that can be investigated relates to innovation policies, and more specifically to government support to R&D. Griffith et al. (2004) unveil a "second face of R&D" showing that R&D not only fosters innovation, but also enhances technology transfers because it increases firms' absorptive

capacity. By engaging in R&D, firms accumulate tacit knowledge that allows them to understand and assimilate existing technology and innovations. However, the concentration of business expenditures in R&D (BERD) suggests that low productivity firms – generally younger and smaller – may also lag in terms of their efforts devoted to R&D. Accordingly, policies supporting R&D expenditures could help laggard firms develop their absorptive capacity. This report focuses on the role of government's direct funding of business expenditures in R&D (with contracts, loans, grants and subsidies) using two different measures. First, government's direct funding of business expenditures in R&D is normalised by GDP to provide a comparable measure of the level of support across countries and over time. Second, a measure of the composition (the source) of R&D funding defined as the share of business expenditures financed by the government over total BERD is used.[69] Results are reported in Table D.17a and Table D.17b for LP and MFP, respectively, and show some evidence (for MFP only) that the level of support to BERD through government direct funding relative to GDP is associated with faster diffusion in digital and skill intensive industries, suggesting that financing R&D can be a lever to increase laggards' absorptive capacity. Importantly, there is even stronger evidence that such support is associated with faster catch-up in digital and skill intensive industries when a higher share of BERD is funded by direct support of the government.

Direct public funding of business expenditures on R&D takes various forms, such as competitive grants, debt financing (loans), risk-sharing mechanisms or public procurements (OECD, 2016a) and these instruments may be particularly relevant for laggards. For instance grants, loans and risk-sharing through credit guarantee schemes can reduce the cost of R&D and improve access to finance for otherwise financially constrained firms.[70] R&D procurement creates a demand for technologies and services that might help young innovative firms, and can also provide early stage financial support before the commercialisation phase (pre-commercialisation procurements of R&D). Each of these instruments may be efficient in promoting R&D expenditure for firms with a potential for growth, but such policies are also part of a broader policy mix that can reinforce the effectiveness of these instruments by exploiting their complementaries (OECD, 2016b).

Overall the results of this section point to three effective areas of policy intervention to boost laggards' absorptive capacity: i) enhancing skills, ii) supporting investment in digital technologies and iii) supporting R&D. The stronger link between these policy objectives and instruments in digital and knowledge intensive industries supports the hypothesis that the digital transformation and the rising importance of knowledge and intangible capital, while overall beneficial for productivity and growth, also raise barriers to diffusion, particularly for SMEs and the least productive firms. Appropriate policies, however, have the potential to lift such barriers. In particular this report provides evidence supporting policy interventions to achieve three objectives:

First, results indicate that a good match between the supply and demand of skills, and low levels of under-qualification, are associated with faster catch-up. Ensuring an adequate supply seems therefore a promising lever to speed up diffusion.

Second, more favourable conditions for SMEs financing seems to support diffusion. This points to a second objective for policies: supporting investment in new technologies for firms with a potential for growth but facing financial barriers to investment.

Finally, the evidence presented in this report suggests that public funding of R&D may speed-up diffusion. This points to a third policy lever to foster diffusion: ensuring that knowledge remains a non-rival good and that firms have the absorptive capacity necessary to exploit it.

6.2. Discussion: developing an ecosystem of policies for technology and knowledge diffusion

In order to foster the diffusion of technology and knowledge, a comprehensive policy mix is required. Policies should aim at creating incentives for firms to adopt new technologies and develop their capabilities, while at the same time supporting innovation. In other words, policies stimulating diffusion and nurturing innovation are, to some extent, two sides of the same coin. This is a direct implication of diffusion models that recognise the role of both demand-side and supply-side determinants of the diffusion process, affecting respectively potential adopters and innovators (such models are reviewed, for instance, by Hall and Khan, 2003; Suriñach et al., 2009; Stoneman and Battisti, 2010). These models highlight that the diffusion of innovation is a continuous and slow process arising from individual decisions to adopt new technologies, after comparing benefits and costs, in an environment characterised by uncertainty and limited information (Hall and Khan, 2003). Policies have the potential to affect costs, benefits and uncertainty associated with adoption by influencing both the demand and the supply of technology and knowledge, as well as the environment in which firms take their decisions.

Studies of the demand-side factors identify three main determinants of adoption, focusing on the role of: i) information on the availability and benefits arising from new technologies; ii) absorptive capacity (the ability to use and adapt existing technology and knowledge); and, iii) factors affecting the profitability arising from adoption, which in turn depends on the price, the expected returns and the risks associated with adoption itself. On the supply side, the diffusion process depends on continuous improvements in innovations to match users' needs, and at the same time on the decline in price of technologies driven by their improvements (as illustrated, for instance, by the decline in the quality-adjusted price of computers), or improvement in production processes. Moreover, the diffusion process can also be shaped by the institutional and regulatory environments, as they may affect firms' profitability and risk of adoption, as well as incentives to innovate.

This section provides a framework to draw policy recommendations to stimulate diffusion, relying on the distinction between demand-side and supply-side determinants. In this framework, "demand-side policies" refer to policies primarily targeting potential adopters and, thus, aimed at: i) increasing their awareness about existing technologies and their benefits; ii) affecting their absorptive and investment capacity; iii) ensuring positive returns to adoption and reduced uncertainty. "Supply-side policies" refer instead to policies supporting productivity-enhancing innovation and, thus, aimed at: i) fostering production and sharing of knowledge; and, ii) enabling experimentation. This framework is summarised in Table 6 and further developed in the next subsection.

Table 6. An ecosystem of policies to foster technology and knowledge diffusion

	Objectives	Instruments
Demand-side	Raising awareness about new technologies, their use and benefits	• Awareness raising schemes • Collaboration and networks • Labour mobility • Trade and GVC participation
	Developing firms' absorptive and investment capacity	• Education system • Training policies (especially for low-skilled) • Financial support • R&D support • ICT infrastructures • Data access
	Favouring positive return to adoption and reducing risks and uncertainties	• Competition policies • Entrepreneurship policies • Insolvency regimes • Normalisation and standardisation procedures • Addressing market failures (networks effects, technological lock-in)
Supply-side	Fostering production and sharing of knowledge	• Public research • Science-industry linkages • Collaboration • Open innovation • Comprehensive strategies for the development of GPTs
	Enabling experimentation and bringing innovations to the market	• R&D support • Entrepreneurship policies • Financial support • IP system • ICT infrastructures • Data access • Test beds and regulatory sandboxes • Open innovation

6.2.1 Demand-side policies affecting potential adopters

Demand-side policies have been grouped into three categories. First, policies can foster diffusion by raising awareness about the existence of certain technologies and their benefits. Second, policies may influence the decision of potential adopters by raising their absorptive and investment capacity, which seem to be insufficient especially among laggards. Third, knowledge and technology diffusion can also be fostered by policies favouring positive returns to adoption and reduced uncertainty.

Raising awareness about new technologies, their use and benefits

Fostering diffusion first requires improving awareness about existing technologies and their benefits, especially among small and young firms, which may be more likely to lack information about new technologies.[71]

Policies may raise firms' awareness directly through dedicated instruments, but also indirectly through an environment favouring important sources of knowledge spillovers. Policy makers can directly increase awareness about digital technologies by exploiting their potential to facilitate the sharing of information. For instance, policy makers may support the development of on-line platforms or virtual maps allowing entrepreneurs to share their experience in engaging in the digital transformation. Awareness can also be improved through business advisory support to inform businesses, especially SMEs, about the existence of particular technologies and their benefits (e.g., cloud computing) and help them identify the best solutions for them. Planes-Satorra and Paunov (2019) present some initiatives developed at the country and European level.

In addition to instruments specifically directed to increase awareness, policies can also reach this goal by putting laggards in contact with many sources of knowledge, and by favouring the circulation of information. In particular, encouraging collaboration, creating networks, and sustaining labour mobility are key elements for innovation (Breschi and Lissoni, 2003; Breschi and Lissoni, 2006) but may also help spread information about technologies and therefore stimulate diffusion, given the importance of "word-of-mouth" for the diffusion process (Dodson and Muller, 1978).

Trade and participation in global value chains (GVCs) are also significant sources of knowledge spillovers. Therefore, policies deepening GVCs participation may bolster technology adoption (see Criscuolo and Timmis, 2017, Suriñach et al., 2009 and references herein). In addition, evidence shows that higher centrality of sectors and countries in GVCs benefits more firms further behind the frontier, through both forward and backward linkages (Criscuolo and Timmis, 2018). This evidence implies that, although connecting the least productive firms to GVCs may be challenging, increasing participation in GVCs may especially benefit laggards through indirect spillovers (for instance through domestic supply of exporters).

Developing firms' absorptive and investment capacity

Addressing the lack of diffusion requires increasing firms' absorptive capacity and their ability to meet the cost of adoption. The diffusion of innovation is, indeed, strongly related to firms' cost of adoption and absorptive capacity, which determine their ability to use and adapt innovations. Given that significant investments may be required to build absorptive capacity, cost of adoption and absorptive capacity are jointly examined here.[72] Several policies areas are identified as particularly relevant

to increase absorptive capacity of firms and stimulate investment: (i) developing human capital; (ii) alleviating financial barriers; (iii) enabling access to good ICT infrastructures and complementary inputs; and (iv) promoting R&D.

First, policies should aim at increasing absorptive capacity through higher investment in human capital and encourage firms, especially laggards, to upgrade workers' skills in order to ensure their technological readiness. The importance of developing technical skills among (potential) users has been recognised early in the literature (Rosenberg, 1972) and is still acknowledged as a significant determinant of adoption, including for technologies that may particularly benefit laggards, such as cloud computing (OECD, 2019a, DeStefano et al., 2019, Andrews et al., 2018). On the one hand, policies may focus on ensuring an adequate supply of specialised high-skilled workers through the education system, and relax competition for talent that may be a significant challenge for laggards. As an example, national strategies on Artificial Intelligence including the development of AI talents (e.g., through the creation of masters and Ph.D. programs) illustrate how the education system can take into account changing skill requirements. Such strategies seem particularly relevant to improve the diffusion of general purpose technologies. On the other hand, ensuring a broad availability of basic digital skills in the workforce and especially among low-skilled workers is still a pressing issue, as illustrated by the significant share of adults who lack basic ICT skills across OECD countries (OECD, 2013). Addressing this challenge requires a wide range of coordinated policies fostering lifelong training for all (OECD, 2019b). This may include efforts to broaden the curriculum and include digital skills in primary and secondary education but also efforts to train teachers. Importantly, policies should also address current skill mismatches by improving access to training for low-skilled workers and adults marginally attached to the labour market.

Second, adoption is costly and appropriate policies are needed to lift financial barriers to adoption, particularly for laggards that may face tighter financial constraints due to their size and age. Adopting new technologies is costly because of the direct cost of investment (e.g., investing in hardware or industrial robots), but also (and likely more) because complementary investments are needed (e.g., investments in software and human capital). This issue may be particularly binding in a knowledge-based economy, given that investments in intangibles assets may be more severely affected by financial constraints (Demmou et al., 2019).[73] Some instruments seem particularly relevant to help laggards undertake their digital transformation. This is the case, for instance, of "innovation vouchers", small non-repayable grants to SMEs to help them implement small-scale projects, such as developing e-commerce and e-skills, or introducing new ICT-based business models (Planes-Satorra and Paunov, 2019). Financial support may also take the form of co-funding of large-scale investments in digital technologies and infrastructures (although laggards are less likely to benefit from them). Finally, loan-guarantees for selected firms, reducing financial constraints related to both the lack of collateral investments and the asymmetry of information, may also facilitate laggards' access to finance.

Third, policies can foster diffusion by ensuring that laggards can access both the appropriate ICT infrastructures and the complementary inputs necessary to adopt more advanced digital technologies. Notably, high-speed broadband infrastructures play a key role in the adoption of: hardware; productivity enhancing software (such as, for instance, Enterprise Resource Planning or Customer Relationship Management software); and digital services, such as cloud computing (see OECD, 2019a, DeStefano et al., 2018, DeStefano et al., 2019, Andrews et al., 2018, and references herein). Beyond appropriate ICT infrastructures, polices may foster diffusion by improving firms' access to complementary inputs such as data, which have become an increasing source of value. Despite the non-rivalrous nature of

data, firms may indeed face legal or strategic barriers preventing firm accessing data. Such barriers could reinforce the productivity divergence by slowing down the diffusion of data intensive technologies, and especially general purpose technologies such as artificial intelligence. Policies could, therefore, aim at improving access to different types of data (personal data, business data, government data, etc.), for instance by supporting data sharing or by developing markets for data while taking into account issues related to privacy protection and cybersecurity (OECD, 2019a).

Fourth, R&D policies can support the development of firms' absorptive capacity and, consequently, may help start-ups and SMEs with a growth potential to benefit from knowledge spillovers. R&D policies primarily aim at supporting innovation, but can also foster adoption by increasing firms' ability to identify, adapt and use new technologies and knowledge (Cohen and Levinthal, 1989, Griffith et al., 2004). This "second face of R&D" implies that the potential benefits of those R&D policies, when also directed to SMEs and start-ups, may go beyond the direct positive effects on innovation. However, at the moment R&D policies do not benefit all laggards, given that most small firms do not engage in formal R&D activity. Complementary policies to R&D, such as promoting collaboration, raising awareness and developing networks, foster collaboration with university and public research institutes may nonetheless help diffuse the benefits of R&D policies to non-innovative laggards through positive spillovers from innovative SMEs and start-ups and universities, or forward and backward linkages with R&D performing firms. Finally, some instruments may be particularly relevant to support R&D activity of young firms and SMEs, such as R&D grants alleviating financial constraints, or R&D procurements reducing the risk of innovative activities (as it provides a stable source of demand).

Favouring positive return to adoption and reducing uncertainty

The third category of demand-side factors influencing diffusion relates to expected returns and risks of adoption, which depends not only on firms' characteristics, but also on market features and the regulatory and institutional framework in which firms operate.

Policies affecting competition and the reallocation of resources are key to ensure that firms can reap the benefits of technology adoption. Demand-side models have indeed pointed to the role of firm size, market shares, and market power as important determinants of adoption, given that they directly affect its profitability. This may be particularly true for investment in digital technologies characterised by significant fixed costs but low marginal costs, which induce increasing returns to scale. To promote diffusion, successful adopters should be able to scale-up rapidly and also benefit from the possibility opened by digital technologies to "grow without mass" to recoup the cost of innovation and adoption (Brynjolfsson et al., 2007). Therefore, possible relevant reforms in this direction include removing barriers to trade and investment, by addressing the regulatory protection of incumbents, or by adapting the employment protection legislation (affecting resource reallocation), but also more generally by lifting barriers to entrepreneurship (given that new firms are more likely to be born digital).

Demand-side models also recognise the role of risk and uncertainty in the decision to adopt innovations, especially among small and young firms, for which uncertainty is even more pressing due to fewer opportunities for risk diversification. A number of policies discussed previously, such as providing expertise but also financial support, may help reduce the risk associated with adoption. In addition, the legal and institutional framework also shapes incentives to engage in risky investments. Previous evidence suggests that insolvency regimes that do not sanction business failure too severely, as well as efficiency of the judicial system, are likely to encourage entry and scale-up dynamics and may

disproportionately benefit laggards (Calvino et al., 2016; McGowan et al., 2017; Andrews et al., 2018). Other instruments, such as normalisation and standardisation procedures, may also reduce the risk of adoption and facilitate the emergence of networks effects, further raising the benefits of adoption.[74]

Overall, demand-side analyses of diffusion imply that a wide range of policies have the potential to foster diffusion by increasing firms' awareness about existing technologies, but also by influencing their ability to invest and use such technologies, and by reducing risks associated with adoption. These policies are primarily concerned with increasing the demand of technology by followers and laggards, their capacity to invest and to use existing technologies. However, diffusion models have also recognised the importance of the supply side, stressing the need for innovation policies encouraging the development of suitable and affordable technologies.

6.2.2 Supply-side policies affecting innovators

The literature on diffusion has recognised the role of suppliers in improving existing innovations and reducing the price of new technologies, thereby supporting their diffusion. Rosenberg (1972) emphasises the continuity of the innovation process, highlighting that it takes time to translate breakthrough inventions into marketable innovations usable by a large number of firms. This continuous process of secondary inventions plays a critical role for diffusion, but requires a dynamic network of innovators, given that not all firms have the absorptive capacity and financial means to adapt frontier innovations.

It is beyond the scope of this report to provide an exhaustive review of policies fostering innovation.[75]. This report, instead, identifies two broad areas where innovation policies may strongly affect the diffusion of technology and knowledge. Firstly, policies may facilitate diffusion by stimulating the production of knowledge and its circulation, for instance through public research and increased collaboration among all stakeholders of the innovation process. Secondly, policies are also likely to stimulate innovation and facilitate diffusion by enabling experimentation.

Fostering production and sharing of knowledge

Policies may affect both innovation and its diffusion by supporting the production of knowledge, through encouragement of research, as well as collaboration to increase knowledge flows. Such policies may help increase the technological impact of an innovation and its legitimation time, or in other terms the depth and speed of diffusion, the two key features of diffusion trajectories. Looking at follow-on inventions, Pezzoni et al. (2019) provide new evidence on the determinants of secondary inventions. According to this evidence, novel technologies that combine similar ideas, and ideas that the inventor's communities are more familiar with, diffuse more rapidly but have a lower technological impact. On the contrary, science-based innovations have a higher legitimation time (slower diffusion) but a significantly broader impact. Supporting science-based innovation, enlarging networks and promoting collaborations could affect diffusion trajectories and achieve the purpose of increasing both the impact of innovation and the speed of diffusion.

Creating an innovation ecosystem, based on a strong public research system and dynamic and diversified collaboration (for instance, between firms, universities and public research organisations) could indeed contribute to increase both the speed and scope of technology diffusion. Some policies seem particularly relevant from this perspective. Promising avenues include optimising the efficiency of

public research, and reinforcing science-industry linkages and business-to-business collaborations. This would stimulate not only innovations with a large technological impact, which would diffuse more widely, but also technological transfers. This objective could be achieved, for instance, by creating collaborative research and innovation centres, by developing collaboration facilitators (intermediary organisations, networks and clusters), by fostering open innovations (through crowdsourcing, open challenges and living labs), and by providing financial support for collaborative R&D (see Planes-Satorra and Paunov, 2019, for examples of such initiatives). In addition, the development and diffusion of such technologies may also be facilitated by initiatives supporting the development of general purpose technologies, such as the adoption of national Artificial Intelligence strategies.[76]

Enabling experimentation and bringing innovations to the market

Experimentation is key to develop secondary innovations, deepen the range of applications for initial inventions, and bring them to the market. In other words, fostering experimentation may be necessary to adapt existing technologies and make them usable and affordable to as many firms as possible, including laggards.

R&D support, competition policies (especially removing entry barriers), policies aiming at providing enough financial resource to start-ups (e.g., through loan guarantees, venture capital, etc.), as well as insolvency regimes are still relevant instruments to support experimentation and entrepreneurship, important drivers of innovation. While the policy framework to support innovation is still relevant, some instruments may nonetheless need to be adapted to respond to the challenges raised by the digital transformation. This is the case of the IP system designed for inventions embodied in physical products and processes. In a similar way, R&D policies, while still very relevant, may be less suitable to provide support to service innovation that are less “R&D based”.

More specific instruments are also available to enable experimentation and promote real-world applications of innovation in digital technologies, a key requirement for the diffusion process. For instance, test beds allow to test new technologies in controlled but near to real-world conditions, and regulatory sandboxes allow firms to test new business models and may prove particularly useful to encourage innovation in services. Another relevant challenge for policy in the digital age is to enhance data access, since innovation has become more data-driven. More generally, policies can foster experimentation by providing start-ups and SMEs with suitable digital infrastructures, as well as advanced research and testing facilities.

Overall, there seems to be a complementarity between support to innovative firms and support to laggards. While the specific instruments may differ, supporting diffusion and innovation are two sides of the same coin, and require a balanced policy mix. However, the combination of the increased productivity dispersion and the slowdown in laggards’ catch-up over time shown in the report, seems to suggest that rebalancing the policy mix to reinforce diffusion mechanisms may be a pressing issue. To summarise, the evidence presented in this report and the review of possible determinants of technology diffusion suggest that policies could focus on: i) raising awareness about the benefits of existing technologies; ii) developing absorptive capacity, increasing human capital at all levels of the workforce and increasing investment capacity; iii) supporting business dynamism and ensuring that markets remain contestable; iv) promoting innovation to develop suitable and affordable technologies.

7. Conclusions

A growing body of literature has shown that the well-known slowdown in productivity growth has been accompanied by an increased divergence in productivity between high productivity firms and laggards (Andrews et al., 2016; Berlingieri et al., 2017b). Recent studies look at the characteristics of firms that operate at the global productivity frontier, and at their relationship with other firms in the economy (Andrews et al., 2015; Andrews et al., 2016). However, they are mainly focused on the distinction between top performing firms and the rest of the productivity distribution. Little is known about the characteristics of firms that operate at the bottom of the productivity distribution (the so-called laggards firms), or about their growth performance over time. Even less is known about how their performance affects aggregate productivity (growth), and which are the structural factors and policies that might help laggard firms close their productivity gap with the frontier.

This report tries to bridge this gap in the literature by focusing more closely on the left tail of the productivity distribution, i.e., on laggard firms, i.e the 40% least productive firms in a country, industry and year. It takes advantage of a novel dataset containing harmonised microaggregated statistics for 13 countries over the last twenty years, based on the OECD MultiProd project. Using these data, the report first investigates the characteristics of laggards and then analyse the role of barriers to technology and knowledge diffusion in slowing down the catch-up of laggard firms.

Looking at the main characteristics of laggards, this report finds that they are on average smaller and younger than the median firm. This result implies that the left tail of the productivity distribution is partly populated by (small) young firms with a potential for growth. Moreover, using a productivity growth decomposition firstly introduced by Melitz and Polanec (2015), the report shows that entry and exit occur mainly at the bottom of the productivity distribution, and that reallocation of resources plays a particularly important role for laggards. The combination of these results suggests that when focusing on the left tail of the productivity distribution an analysis that goes beyond the concept of “representative firm” or “zombie firm” is particularly relevant. A direct implication is that one should be cautious in associating laggards with unhealthy firms, and more so when advocating that low productivity firms should exit the market. Given the high heterogeneity amongst laggards which may range from old firms with ageing technologies to young firms and entrants with a potential for productivity growth, different policies would need to be put in place to address these different cases.

The report then explores the importance of laggard firms for aggregate productivity. A counter-factual exercise shows that increasing (labour) productivity of laggards (p(10-40) in this case) to the level of the median firm could increase aggregate productivity by 6%. The exercise entails an increase in productivity of 60%, which is certainly not negligible but potentially achievable given the low initial productivity of these firms. In addition, this report confirms that low productivity firms grow faster than firms with already high productivity.

The catch-up of laggard firms is further explored by looking at the relationship between their productivity growth and their distance to the frontier (the productivity gap). This analysis confirms a positive relationship between the productivity gap and productivity growth of laggards, indicating that firms which are further behind the national frontier experience on average higher rates of productivity

growth. In addition, younger laggards catch up faster, highlighting that the composition of the laggard group matters for the future of productivity. However, the speed of catch-up has decreased over time.

Therefore, this report investigates whether catch-up gets slower as the importance and exposure to digital technologies and knowledge increase. It provides robust evidence that laggards are catching up at a lower speed in industries characterised by more intensive use of digital technologies and digital skills, as well as in industries characterised by higher average levels of (general) skills, suggesting obstacles to the transfer of technology and knowledge. These barriers to diffusion, by slowing down the speed of catch-up, may also be a cause of the increase in productivity dispersion. This report sheds further light on the decline in knowledge diffusion documented in the literature (Andrews et al., 2016, Akcigit and Ates, 2019a, Akcigit and Ates, 2019b) by suggesting that the digital transformation and the transition to a knowledge economy are associated with rising barriers to diffusion.

These results raise key questions about why seemingly non-rival technologies and knowledge do not diffuse to all firms. The evidence gathered in this report suggest that structural factors such as skill intensity and digitalisation, although potentially beneficial for overall growth, may not benefit to all firms equally. They also suggest that laggards, not having the necessary absorptive capacity and not facing proper incentives, may have more difficulties catching up in industries where technology and knowledge matter the most.

Appropriate policies, however, may have the potential to lift such barriers. Firstly, results indicate that a good match between the supply and demand for skills, and low levels of under-qualification, are associated with faster catch-up. Ensuring an adequate supply of skills seems therefore a promising lever to speed-up diffusion, and the report shows that training policies may be relevant instruments to ensure that workers have the relevant skills sought by firms. The digital transformation and the transition to a knowledge economy reinforce the need for policies aimed at ensuring a good match between the (changing) demand of skills and its supply. Secondly, the report indicates that more favourable conditions for SMEs financing are also a potential important policy tool to support diffusion. However, the heterogeneity amongst laggards highlighted in this report suggests that one size does not fit all, and hence this result does not imply that financial support based exclusively on firm size is necessarily beneficial. It rather indicates that supporting investment in new technologies, intangible assets and human capital, for firms with a potential for growth but constrained by financial barriers, may help speed-up the process of knowledge and technology diffusion. Finally, the report also suggests that public funding of business expenditures in R&D (through grants, loans, procurements, etc.) may also speed-up diffusion by creating a demand for technologies and also by providing financial support to young and small, potentially financially constrained, firms.[77]

Finally, the report outlines a framework to draw policy recommendations to stimulate diffusion, relying on the distinction between demand-side and supply-side determinants. Demand-side policies focus on potential adopters, and should aim at: increasing awareness about technologies; raising the absorptive and investment capacity of laggards; and, ensuring that successful adopters can reap the benefits of their digital transformation, while at the same time reducing the risks and uncertainties associated with adoption. Supply-side policies include policies supporting productivity enhancing innovation and, thus, aimed at fostering production and sharing of knowledge and enabling experimentation.

Notes

[1] See Hsieh and Klenow (2010) and Hopenhayn (2014) for a more recent review of the literature.

[2] Note that not all young firms are operating below their efficiency scale. Some may be developing their products or exploring their prospects for success. Many of these firms can be expected to exit rapidly after entry, as they discover the market potential of their products. This process of experimentation contributes to business dynamism and is closely related to the entry of firms with a growth potential.

[3] MultiProd collects data for all sectors of the economy, whenever available. However, not all sectors are available in all countries. Therefore, for the purposes of this analysis the sample is restricted to manufacturing and non-financial market services. In addition, in order to guarantee the comparability across deciles of the productivity distribution and across macro-sectors, the sample is further restricted to those countries providing productivity statistics representative of the whole population of firms. Given the focus of this report on the bottom part of the productivity distribution, it is important to include in the sample only countries where the whole distribution of firms is well represented. Therefore, we exclude from the analysis all countries which impose a threshold for inclusion of firms in the sampling frame. See further details in Section 2.

[4] MultiProd, DynEmp, and MicroBeRD are projects carried forward by the Directorate for Science, Technology and Innovation (STI) at the OECD. The DynEmp (Dynamics of Employment) project provides harmonised micro-aggregated data to analyse employment dynamics (find out more: http://www.oecd.org/sti/dynemp.htm) and MicroBeRD provides information on R&D activity in firms from official business R&D surveys (find out more: http://www.oecd.org/sti/rd-tax-stats.htm).

[5] The program works also in the absence of a business register. Further details about the representativeness of the MultiProd dataset, as well as a comparison with the STAN dataset, can be found in Bajgar et al. (2019).

[6] Macro-sectors are defined according to the STAN A7 classification and detailed industries follow the STAN A38 classification (based on ISIC Rev. 4, SNA08). The non-financial market service sector includes the following 2-digit industries: Wholesale and retail trade, repair of motor vehicles and motorcycles; Transportation and storage; Accommodation and food service activities; Publishing, audiovisual and broadcasting activities; Telecommunications; IT and other information services; Legal and accounting activities; Scientific research and development; Advertising and market research, other professional, scientific and technical activities, veterinary activities; Administrative and support service activities.

[7] Note that the productivity groups used here are not equally sized.

[8] See Table D.5 for a table distinguishing between manufacturing and non-financial market services. This table shows that services firms are on average younger and much smaller than manufacturing ones in every productivity group. Moreover, the relationship between productivity and firm size is much weaker in services than in manufacturing. A greater share of service sector workers are employed in firms in the bottom part of the LP distribution. In services, 33% of total employment is in firms with the lowest 40% of the productivity distribution, compared to 20% in manufacturing.

[9] For the sake of maximising cross-country comparability we rely on headcounts (HC) for measuring labour input, since it is the measure most commonly available in the countries considered. When HC is not available we rely on full time equivalents (FTE).

[10] For a detailed discussion on control function approaches, see Ackerberg et al. (2007).

[11] For brevity and clarity of the presentation, descriptive results detailed in this section are presented for labour productivity only, and using mostly graphical representations. Additional tables and figures, displayed in the Appendix (and indicated in the main text) also provide further details for both labour productivity and multi-factor productivity, whenever relevant.

[12] While in manufacturing productivity increases significantly with firm size, this relationship does not hold for services. For further reading on this topic, see Berlingieri et al. (2018a) and Berlingieri et al. (2018b).

[13] Similar characteristics have been highlighted in Ardanaz-Badia et al. (2017) for Great Britain over the period 2003–2015: among firms in the bottom 10% of the labour productivity distribution, roughly 93% of businesses had fewer than 10 employees, and 44% were aged 1 to 5 years (and a further 20% were no more than 10 years old), highlighting that young and micro firms are overrepresented among the 10% of firms with the lowest productivity.

[14] Results for MFP are very similar to those obtained for LP, both in terms of size and age, the only exception being the size of firms in the top decile of the productivity distribution. Firms belonging to the top decile of the MFP distribution are on average bigger than firms belonging to the top decile of the LP distribution.

[15] Table D.6 reports the results from a regression of average age and size on a categorical variable with values representing each productivity (either LP or MFP) group, including country-2-digit industry-year fixed effects. These estimates capture the average difference in terms of size and age for a given productivity group with respect to the median one. The regressions also show more pronounced age and size differences in the upper part of the MFP distribution compared to the LP distribution. The large size difference of the top 10% firms in terms of MFP reflects the presence of some very large firms at the MFP frontier (unreported results based on median firm size, rather than the mean, display smaller size differences between firms at the top of MFP distribution and the rest).

[16] Foster et al. (2008) and Foster et al. (2016) show that it might also reflect the fact that start-ups need to build reputation, i.e., a lack of intangible assets such as brand reputation rather than technological efficiency. In addition, the observed low productivity of entrants may also be related to a downward bias in the estimation of their real productivity due to the use of revenue multi-factor productivity (RMFP) and the overestimation of their output price. Firm specific prices are indeed usually unobserved, and hence researchers use industry-wide price deflator. By looking at specific industries where plant-specific prices are observed, Foster et al. (2008) show that entrants typically price below the average incumbent. Therefore, revenues deflated by industry prices will lead to an underestimate of entrant output and, consequently, productivity.

[17] This link between age, size and productivity is consistent with predictions from models of market selection and learning (Jovanovic, 1982, Hopenhayn, 1992, Ericson and Pakes, 1995). According to these models firms learn their productivity only after entering, and either quickly exit, if they belong to the low productivity type, or expand rapidly. Accordingly, not all young low productivity firms operate below their efficiency scale, as some of them are just experimenting and quickly exiting the market.

[18] Unfortunately it is not yet possible to estimate the composition of the laggard group and the relative importance of each type of firm. A future version of the MultiProd dataset will include transition matrix that will allow such quantification.

[19] A similar relation is found for laggard firms surviving at least 5 years, i.e., when looking at the (annualised) average firm-level productivity growth between *t* and *t+5*.

[20] On average, 57% of laggard firms survive at least five years.

[21] It is worth noting that the entry and exit components, the last two terms in the decomposition, capture true entry and exit in the market, and not in a particular productivity group.

[22] The formula omits the index for countries given that the decomposition is performed on each country individually, and then averaged across countries.

[23] The Olley and Pakes (1996) covariance term, also called OP gap, has been used as a measure of allocative efficiency. It increases if more productive firms capture a higher share of resources in the sector.

[24] It is worth noting that the fact that entrants have productivity lower than incumbents, even in the bottom decile of the distribution, might be due to the aforementioned underestimation of their real productivity (Foster et al., 2008).

[25] Both Figure 5 and Figure C.7 point to very similar contributions of entry, exit, reallocation and incumbents to, respectively, LP and MFP growth in different parts of the productivity distribution. There is, however, a noticeable difference regarding the sign of the contribution of reallocation to productivity growth at the frontier. This difference can be related to the use of different measures of size for the decomposition of LP and MFP growth. For the decomposition of LP, size is measured in terms of employment while for MFP size is measured in terms of value added. Therefore, for LP the negative contribution of the reallocation term reflects a decrease in the correlation between productivity and size, in terms of employment, at the frontier. On the contrary, the positive contribution of reallocation at the MFP frontier reflects an increase in the correlation between value added and productivity. This difference might be consistent with "scale without mass" dynamics, whereby ICT permit gaining market shares with fewer workers. In particular, new entrants (usually smaller) have the possibility to more rapidly leap-frog and displace leaders (Brynjolfsson et al., 2007).

[26] This productivity enhancing effect of market selection is stronger at the beginning of the life-cycle (i.e., for young firms), because young firms have a larger productivity gap with respect to incumbents.

[27] Future version of the MultiProd code will implement transition matrices that would allow further investigations of these dynamics.

[28] Note that this exercise and the following one are performed only on labour productivity. In principle it can be generalised to MFP, but the choice of the appropriate weights becomes less straightforward. In the literature it is common to use output weights (GO or VA depending on how MFP is estimated), but the resulting weighted average does not correspond to the precise measure of aggregate productivity.

[29] Since the data in MultiProd are micro-aggregated moments (and means in particular) from firm-level data, in all regressions we weight each observation cjq,t by the number of firms reporting non-missing information for the relevant variable in a given country-industry-year-productivity group. The weighting strategy implies that our estimates are equivalent to those hypothetically generated using the underlying micro-data samples.

[30] While factors affecting the strength of the catch-up may be country, industry, productivity group and time variant, the main regressions presented in the report focus on variables varying only at the industry level, in order to focus on structural characteristics and to circumvent some data limitations. Measures varying only at the industry level are therefore denoted by X_j.

[31] In particular it accounts for serial correlation of the residuals and correlation across productivity groups within the same country and industry.

[32] However, extensions of this work could explore the role of the global frontier as well.

[33] Digital industries are those that are in the top quarter of the digital intensity distribution of industries in either 2001-2003 or 2013-2015. See Calvino et al., 2018 for additional details.

[34] It is worth noting that Calvino et al. (2018) show that these indicators are imperfectly correlated and, as such, measure complementary facets of the digital transformation.

[35] For the machinery production sectors (ISIC revision 3 sectors 29 to 35), purchases of ICT intermediate goods are set to missing. ICT purchases in these industries are likely to be microchips or electronic components, used in the production of goods that are subsequently sold-on to other consumers, and so are not used by the producing firms as a “substitute” or “complementary” to investment.

[36] In a previous version of the report, the human capital dimension was proxied by the share of ICT specialists, which is particularly high for the IT industry. In the current version, the ICT task intensity has been preferred, given that it displays more variation in other industries and better accounts for the use of ICT across a broader range of occupations.

[37] The data on skills, available at country-industry-year level, are ISIC Revision 4 estimates based on the ISIC 3 original data from the World Input Output Database (WIOD), Socio Economic Accounts, July 2014 (see Timmer et al., 2015).

[38] The underlying variable is missing for two countries in the sample (Norway and Switzerland) and is available until 2009 only for other countries in the sample.

[39] Regarding knowledge intensity, concerns of endogeneity could also arise from reverse causality due to skill-biased technological change.

[40] Despite this advantage of using a benchmark country to compute the measure, measures of digital intensity available from Calvino et al. (2018) are based on cross-country data.

[41] For more details, see https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm.

[42] The size of the coefficient implies that a 10% increase in the productivity gap ($\frac{A_F}{A_q}$ in Equation (7)) between frontier and laggards is associated to a nearly 2 percentage points increase in the productivity growth of laggards.

[43] The variable represents the average age of firms within a cell, i.e., in a given country-industry-productivity performance group-year.

[44] The interaction term between MFP gap and age is not confirmed in this setting. This is likely to be due to the fact that the most relevant differences in terms of age across productivity performance groups (see Figure 3) have been absorbed by the modified fixed effects.

[45] Obviously, no causality can be inferred from these graphs. On the one hand large firms may be able to adopt more easily new technologies; on the other one, it is also possible that early adoption allows firm to become larger faster.

[46] The figure plots the coefficients from a regression similar to Equation (8) when the productivity gap is additionally interacted with year dummies. The analysis focuses on the period 2000-2012 in order to limit the effect of differences in coverage across

countries. Table D.10 presents the results of the underlying regressions and shows that the decline in the speed of convergence is statistically significant (at least in the last years).

[47] Andrews et al. (2016) find a stronger decline in diffusion when focusing on a measure of MFP corrected for mark-ups.

[48] Ten empirical regularities are reviewed in the aforementioned papers. 1) Market concentration has risen. 2) Average mark-ups have increased. 3) Average profits have increased. 4) The labour share of output has gone down. 5) The rise in market concentration and the fall in the labour share are positively associated. 6) The labour productivity gap between frontier firms (defined as the top five percent of firms with the highest productivity level) and to the rest (laggard firms) has widened. 7) The firm entry rate has declined. 8) The share of young firms in economic activity has declined. 9) Job reallocation has slowed down. 10) The dispersion of firm growth has decreased.

[49] Differences in digital and knowledge intensity may be associated with different levels of productivity growth in all parts of the distribution. This direct effect of digital technology and knowledge intensity on the productivity growth of laggards is accounted for by the industry fixed effects.

[50] The global taxonomy takes into account differences regarding tangible and intangible investments in ICT, purchases of ICT intermediates, the share of ICT specialists, ICT task intensity, the use of robots and the share of revenues from online sales. See the previous subsection for a more detailed description.

[51] Considering LP, the coefficients imply that a 10% increase in the productivity gap ($\frac{A_F}{A_q}$) is associated with a 2.2 percentage point increase in the productivity growth of laggards in non-digital intensive industries . In a digital industry, a 10% increase in the gap is associated with a 1.6 percentage point increase in laggards' productivity growth.

[52] Geographical disparities in access to enabling infrastructures may be an important barrier to catch-up if laggards are more represented in less favoured areas.

[53] In reality, the average gap also varies across industries, so using industry specific averages would also be relevant since productivity growth depends on both the speed of catch-up and the productivity gap. In order to avoid mixing the two effects, the report focuses on differences in the speed of diffusion only.

[54] This exercise is performed considering low and high values of X_j as the 10^{th} and 90^{th} percentiles of X_j when it is a continuous variable or corresponding to 0 and 1 when X is a dummy variable.

[55] As explained in Section 4.2, measures of digital and skill intensity are computed at the industry level and are similar for all countries and fixed over time, due to data availability and exogeneity concerns. This comes at the price of limited variation of these indicators, as illustrated in Figure C.12 of the Appendix. It in turn makes it difficult to clearly disentangle the link between each factor and the speed of catch-up.

[56] This correlation can affect the estimates due to collinearity issues.

[57] The correlation between the two variables may lead to inflated standard-errors, possibly explaining why each interaction separately is not statistically significant.

[58] The reader should keep in mind the limitations induced by the correlation of the different measures.

[59] The robustness checks show that the results are robust to: i) excluding ICT producing industries; ii) using productivity gap lagged by three periods (to mitigate concerns related to the measurement error); iii) using alternative definitions of productivity growth taking into account longer time horizons (to mitigate concerns on mean reversion); iv) including a measure of capital intensity and a more restrictive set of fixed effects (to mitigate concerns on omitted variable bias); v) restricting the sample period to a later period (to mitigate concerns on reverse causality). See more details in Appendix B.

[60] Future analysis could look at *changes* in dispersion. This would require, however, a measure of *changes* in digital and knowledge intensity within country-industries, which is more challenging in terms of data availability.

[61] In the following, the term policy is used to refer to both policy objectives which are not directly under the control of governments (e.g., reducing mismatch between skill supply and demand) and policy instruments (e.g., support to training) that can be used by governments to achieve these objectives.

[62] The term effect is used for brevity to refer to the correlation between Pol and the strength of the catch-up effect, without necessarily implying causality.

[63] Therefore, interpretation of the coefficient β_2 is different from the one given in Section 5, where it could be interpreted as the average effect of the digital and knowledge intensity indicators on the speed of catch-up.

[64] In this respect, the coefficient β_5 cannot be interpreted directly as it does not have the same interpretation as in the difference-in-differences framework initiated by Rajan and Zingales (1998). Firstly, because the differential effect between high and low exposure in country-years with high levels of policies compared to country-years with low levels of policies now depends on the level of the gap, and is given by $(\beta_5 + \beta_4 \times gap) \times (X^{high} - X^{low}) \times (Pol^{high} - Pol^{low})$. The coefficient β_5 would therefore be the difference-in-differences estimate of the effect of the policy when the gap is nil, which never happens in this sample given the focus on laggards (a corollary of this is that the sign of β_5 cannot be interpreted as the direction of the policy effect). Secondly, the analysis focuses on the effect of policies on industries that face particular barriers due to digital and skill intensity, which are not necessarily the more sensitive, or exposed to the policy considered. For instance, the analysis investigates whether innovation policies increase the speed of diffusion in digital and skill intensive sectors by increasing firms' absorptive capacity, but do not evaluate the direct productivity gains arising from increased R&D support.

[65] Results are robust to using the alternative measures of digitalisation and skill intensity considered in the paper.

[66] The level required in a job is based on the modal education level for all workers in the same occupation.

[67] This indicator includes levels of underqualification and overqualification. While overqualification could indicate a high level of education in the country, it also reflects a poor match between skills and jobs. As such, both underqualification and overqualification are relevant to quantify skills mismatch.

[68] This variable is the sum of spending for institutional training, workplace training, integrated training, special support for apprenticeship. It corresponds to spending on labour market programmes that are targeted on the unemployed (and possibly on closely-related groups). The targeting criterion excludes training that is generally available to employed adults (the subcategory "Workplace training" should not be understood to include such training), except when participation is funded (in terms of tuition fees or payment of a training allowance or unemployment benefit) due to membership of a target group.

[69] These measures are sourced from the OECD Science Technology and Industry Outlook.

[70] Unreported evidence shows no positive effect of R&D tax credits on laggards' catch-up. One possible limitation of R&D tax support in this context is related to the design of such policies. To fully benefit also small and young firms, R&D tax incentives should include carryforward provisions, cash refunds or reductions in social security and payroll taxes. Differences in the design across countries and over time are not taken into account. Appelt et al. (2016) and Appelt et al. (forthcoming) discuss the role and effectiveness of different types of R&D support.

[71] The lack of information slows down diffusion, as emphasised by "epidemic models" which assume potential users to be homogeneous but differ in terms of when they receive information about the existence of technologies and how to use it (early contributions to this strand of literature include Griliches, 1957 and Mansfield, 1961).

[72] The role of these factors has been emphasised, for instance, by "rank (or probit) models", which rely on agents (firms) with perfect information on technologies and their use, but heterogeneous characteristics resulting in different costs of adoption and different abilities in using new technologies.

[73] In addition, some complex technologies may not necessarily be readily available to use, and potential adopters may need to adapt previous technologies, which in turn involves significant human capital and implementation costs.

[74] Such network effects, together with technology lock-in, may represent important market failures that may deserve further attention.

[75] In addition, thorough reviews of challenges faced by innovation policies in the digital age, as well as existing initiatives to address these challenges, can be found in recent OECD reports (OECD, 2019a; Guellec and Paunov, 2018; Planes-Satorra and Paunov, 2019)

[76] See also Planes-Satorra and Paunov (2019), for a review of existing strategies.

[77] Other innovation related policies that are not investigated in this report may help, such as policies related to IP rights. See Branstetter et al. (2005) and Graham et al. (2014).

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Appendix

A. Theoretical framework

This section outlines the theoretical framework underlying our modelling strategy. There is a conventional output production function in which value added Y is produced according to a standard neoclassical production technology combining productivity and physical input(s):

$$Y_{cjq,t} = A_{cjq,t}\mathscr{F}(Z_{cjq,t}), \tag{A.1}$$

where output Y, productivity A and inputs Z are allowed to vary across countries c, industries j, productivity performance groups q, and time t. If $\mathscr{F}(\cdot) = \mathscr{F}(L_{cjq,t})$, A represents labour productivity. If instead $\mathscr{F}(\cdot) = \mathscr{F}(L_{cjq,t}, K_{cjq,t})$, then differences in capital intensity are accounted for and A represents multi-factor productivity. In the latter case $\mathscr{F}$ is assumed to be homogeneous of degree 1, and to exhibit decreasing marginal returns to the accumulation of each factor alone. The group with the highest average productivity level in each country c, industry j and time t is termed the national frontier ($q = F$).

The model presented follows the empirical literature on R&D and productivity growth (see, for example, Griliches and Lichtenberg, 1984, Griffith et al., 2004), and in particular relies on the model proposed by Griffith et al. (2000) who consider the level of productivity as a function of the stock of R&D knowledge and a residual set of determinants (including for instance human capital). In this report, it is assumed that productivity is primarily a function of technology and knowledge (G). For instance G might denote ICT capital that accumulates as follows: $\dot{G} = I - \varphi G$, I being in this example investment in ICT capital and φ the depreciation rate. Productivity is also a function of other determinants $B_{cjq,t}$ (for instance capturing knowledge diffusion), so that $A_{cjq,t} = \mathscr{H}(G_{cj,t-1}, B_{cjq,t})$.[78] Taking logarithms , differentiating with respect to time, and moving to discrete time,[79] the rate of (labour or multi-factor) productivity growth can be written as:

$$\Delta \ln A_{cjq,t} = \rho_{cj,t} X_{cj,t-1} + \nu_{cjq,t} \Delta \ln B_{cjq,t}, \tag{A.2}$$

where $X = I/Y$, $\rho_{cj,t}$ is the rate of return of marginal product of the investment I in technology/knowledge, which is modelled as having a direct effect on productivity growth. By extension, in the empirical analysis, X will denote factors that directly affect productivity growth.

To analyse more systematically the link between productivity growth and the gap in productivity across firms, we rely on the neo-Schumpeterian growth framework (Aghion and Howitt, 2006). In this model a country's productivity growth at time t is assumed to be a function of its lagged productivity gap with the frontier economy in $t-1$ (catch-up effect) and the contemporaneous rate of productivity growth of the frontier economy at time t, a proxy for the rate of technological progress. The rationale behind the link between productivity growth and the productivity gap (i.e., the distance to the frontier of productivity) is that the gap represents a measure of the potential for learning and spillovers. In other words, productivity growth at the frontier induces faster growth in the rest of the productivity distribution by expanding the production possibility set. Therefore the set of residual factors influencing productivity,

denoted by B, includes productivity growth at the national frontier and the productivity gap with the national frontier, in order to account spillovers and catch-up effects:

$$\Delta \ln B_{cjq,t} = \pi_{cj,t} \Delta \ln A_{cjF,t} - \sigma_{cjq,t} \ln \left(\frac{A_q}{A_F} \right)_{cj,t-1} + u_{cjq,t}, \tag{A.3}$$

where $\ln \left(\frac{A_q}{A_F} \right)_{cj,t-1}$ denotes the relative level of productivity in the productivity quantile q with respect to the frontier (the productivity gap), and $u_{cjq,t}$ is a stochastic error. Since productivity in a non-frontier performance groups lies below the level at the frontier, $\ln \left(\frac{A_q}{A_F} \right)_{cj,t-1}$ is negative. The smaller $\ln \left(\frac{A_q}{A_F} \right)_{cj,t-1}$, the further firms in performance group q lie behind the technological frontier in the same industry, and the greater the potential for technology transfer.

Plugging (A.3) into (A.2) yields an expression for the evolution of productivity in performance group q relative to the national frontier:

$$\Delta \ln A_{cjq,t} = \lambda_{cj,t} \Delta \ln A_{cjF,t} + \beta_{cjq,t} \ln \left(\frac{A_F}{A_q} \right)_{cj,t-1} + \rho_{cj,t} X_{cj,t-1} + u_{cjq,t}, \tag{A.4}$$

where $\lambda_{cj,t} = \nu_{cj,t} \cdot \pi_{cj,t}$ captures the instantaneous effect of changes in frontier growth on growth in non-frontier productivity groups, and $\beta_{cjq,t} = \nu_{cj,t} \cdot (-\sigma_{cjq,t})$ measures the rate of technology transfer.

In equation (A.4), the technology/knowledge taken into account, denoted by X, affects productivity growth only through a direct effect. However, a number of theoretical and empirical papers (for instance, Cohen and Levinthal, 1989, Leahy and Neary, 2007, Griffith et al., 2000, Griffith et al., 2004) have emphasised the importance of absorptive capacity, i.e., a firm's ability to identify, assimilate, transform, and use knowledge, research and practice that exist outside the firm itself. To allow to account for technology transfer to be related to the absorptive capacity of firms, equation (A.4) is extended to allow X to enter the equation both linearly and as an interaction term with the size of the productivity gap. Therefore, the rate of technology transfer in non-frontier performance groups is allowed to be a function of X:

$$\beta_{cjq,t} = \beta_1 + \beta_2 X_{cj,t-1}. \tag{A.5}$$

Substituting (A.5) into (A.4), the preferred model is obtained:

$$\Delta \ln A_{cjq,t} = \lambda \Delta \ln A_{cjF,t} + \beta_1 \ln \left(\frac{A_F}{A_q} \right)_{cj,t-1} + \beta_2 \ln \left(\frac{A_F}{A_q} \right)_{cj,t-1} \times X_{cj,t-1} + \rho X_{cj,t-1} + u_{cjq,t}. \tag{A.6}$$

Notice that, with respect to (A.4), a common coefficient on λ, β, and ρ has been imposed, indicating that the return to an additional unit of X will depend on how far in each country an industry is behind the national frontier $\left(\rho + \beta_2 \ln \left(\frac{A_F}{A_q} \right)_{cj,t-1} \right)$.

B. Robustness and discussion

A number of robustness checks are provided in this section in order to address possible econometric issues, and to corroborate the interpretation that the association between industry characteristics and the lower speed of catch-up reflects barriers to diffusion related to the growing importance of skills and digital technologies.

Use of ICT vs. reallocation towards ICT industries The reports shows that diffusion is slower in industries that are more ICT intensive due to higher barriers in these industries – lack of skills, cost and financing of tangible and intangible ICT investments, growing importance of intangible capital, need for complementary investments. If the digital transformation indeed raises barriers to diffusion, a first question to answer is whether the slower speed of catch-up revealed in Table 4a and Table 4b reflects the growing importance of the ICT sector or barriers associated with the broad usage of ICT also in other sectors of the economy. To answer this, regressions are estimated on a sample excluding manufacturing and service ICT producing industries. The following STAN A38 2-digit industries are excluded: 26 "computer, electronic and optical products", 58-60 "Publishing, audiovisual and broadcasting activities", 61 "Telecommunications" and 62-63 "IT and other information services". Estimates are presented in Table B.1a and Table B.1b and largely confirm previous results, showing that the slower diffusion in digital and skill intensive industries is not driven solely by ICT producing industries. The main results do not reflect a reallocation towards ICT industries and instead suggest that barriers to diffusion is rather related to the importance of ICT in all sectors.

Measurement error, transitory shocks and mean reversion

A common issue in the estimation of the catch-up equation is related to measurement errors. Log-productivity of laggards $P_{cjq,t-1}$ appears on both the left and right hand sides of the regression specification. Measurement errors in $P_{cjq,t-1}$ could therefore leads to a spurious correlation between productivity growth and the productivity gap. To address this concern the gap is replaced by its three period lag $gap_{cjq,t-3}$. This way $P_{cjq,t-1}$ appears only on the left hand side.[80] Results are qualitatively and quantitatively very similar (Table B.2).

A further concern is whether the correlation between productivity growth and the distance from the frontier reflects a productivity catch-up related to diffusion or simply mean reversion dynamics. Such mean reversion can arise from temporary negative productivity shocks that induce both a larger productivity gap and faster growth as productivity is reverting to the equilibrium value. Suppose, for instance, that employment is predetermined and there is a one time negative shock to firms' demand resulting in lower value added. This would result in a negative labour productivity shock, but in the next period the effect of the demand shock disappears and productivity reverts to its equilibrium value, which is reflected in a higher productivity growth.[81] In order to mitigate this concern, similar equations are estimated for an alternative definition of productivity growth taking into account a longer time horizon. More specifically, the growth rate is computed as the average between the annualized growth rates between t and $t+2$, t and $t+3$, t and $t+4$, t and $t+5$.[82] This variable therefore takes into account productivity growth over a 5 year horizon which should attenuate the effect of mean reversion induced by transitory shocks. Note also that this average of annualised growth rates is less subject to measurement errors in a particular horizon $t+j$ than any growth rate based on two years only. Results from this

regressions are displayed in Table D.12a and Table D.12b and confirm both the existence of the catch-up effect for laggards and the lower diffusion in digital and skill intensive industries.

Omitted variable bias Another concern is related to the possibility that the lower speed of catch-up associated with digital and knowledge intensity is induced by other characteristics correlated with the higher digital and/or knowledge intensity, resulting in an omitted variable bias. One particular issue could arise from differences in capital intensity, especially when evaluating the effect of knowledge intensity. Due to embodied technological change, differences in capital intensities may also be associated with differences in the nature and quality of capital. For this reason, limitations in laggards' investment capacity may induce differences in capital accumulation in turn leading to technological gaps and higher heterogeneity in the quality of capital between laggards and frontier firms. While MFP measures control for such differences in firms' capital intensities, the measure used in this paper does not control for differences in the quality of capital. This possible heterogeneity between laggards and frontier firms regarding the quality of capital is likely to increase with the overall capital intensity of the sector. Therefore, given the complementarity between skilled labour and capital, the slower catch-up in sectors characterised by a more intensive use of skilled labour uncovered in columns (7) and (8) of Table 4 could be in fact affected by the omitted interaction between the productivity gap and the overall industry capital intensity. To address this potential issue, results presented in Table B.3 also include an interaction term between the productivity gap and an industry-level measure of capital intensity, the capital-labour ratio.[83] These results show that there is not a significant difference in the speed of catch-up among firms belonging to industries with different level of capital intensity. On the contrary, the estimated coefficients of digital and knowledge intensity – the main coefficient of interest – are robust to including the interaction of the productivity gap with a measure of capital intensity.

Another approach to (partially) overcome the problem of omitted variable is to estimate similar regressions with a more restrictive set of fixed effects. Table B.4 reports estimates from regression including country-sector-quantile and year fixed effects. The results are therefore based on within group regressions, which allow to control for all country-industry-productivity performance group characteristics.[84] This is a very demanding specification but conclusions from these regressions generally confirm that systematic differences between country-sector and across quantiles within sectors are not driving the main results (despite not all interaction terms being significant for MFP).[85]

Reverse causality Finally, one might be concerned that results are affected by reverse causality, casting doubts about the interpretation of the results. Results are interpreted as follows: higher digital and skill intensity of an industry is associated with a lower speed of catch-up because digitalisation and skill intensity raise barriers to diffusion. This interpretation would be erroneous if barriers to diffusion were unrelated to digital and skill intensity but at the same time were inducing a transformation of the industry, leading to the high digital and skill intensity observed at the industry level.[86] Such concerns – that seem rather unlikely – should be mitigated by re-estimating the equation on a sample period restricted to a later period.[87] In addition, measures of digital and skill intensity are based on cross-country or benchmark country indicators and are therefore hardly affected by country specific barriers (e.g., regulation). Table D.13 presents estimates based on a sample starting in 2005, which leads to very similar results.[88, 89]

Table B.1. Productivity growth and catch-up of laggards: digital and knowledge intensity, excluding ICT industries

(a) Labour productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
LP gap	0.1988***	0.2232***	0.2223***	0.1933***	0.2179***	0.1924***	0.2029***	0.1856***
	(0.017)	(0.014)	(0.015)	(0.018)	(0.015)	(0.018)	(0.016)	(0.019)
LP gap × X	-0.0319**	-0.0346**	-0.0342***	-0.0365**	-0.0389***	-0.0433***	-0.0378***	-0.0419**
	(0.015)	(0.014)	(0.011)	(0.014)	(0.014)	(0.015)	(0.014)	(0.017)
Adj. R-Square	0.753	0.752	0.767	0.749	0.759	0.757	0.761	0.761
Observations	4930	4930	4930	4183	4930	4930	4930	2052
Num countries	13	13	13	13	13	13	13	13
LP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

(b) Multifactor productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
MFP gap	0.1525***	0.1687***	0.1662***	0.1405***	0.1647***	0.1404***	0.1562***	0.1448***
	(0.013)	(0.014)	(0.013)	(0.021)	(0.013)	(0.019)	(0.012)	(0.015)
MFP gap × X	-0.0371***	-0.0308**	-0.0278**	-0.0282	-0.0339**	-0.0352**	-0.0393***	-0.0472***
	(0.014)	(0.015)	(0.011)	(0.017)	(0.014)	(0.017)	(0.013)	(0.015)
Adj. R-Square	0.505	0.491	0.503	0.476	0.497	0.489	0.512	0.505
Observations	4478	4478	4478	3769	4478	4478	4478	1723
Num countries	13	13	13	13	13	13	13	13
MFP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

Note: LP (MFP) growth top firms corresponds to LP (MFP) growth between *t-1* and *t* of firms in the top decile of the LP (MFP) distribution at time *t-1*. LP (MFP) gap is computed as the difference between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). All variables *X* are standardized, except in columns (1) and (8) where *X* denotes dummy variables. Manufacturing and non-financial market services only. The following STAN A38 2-digit industries are excluded: 26 "computer, electronic and optical products", 58-60 "Publishing, audiovisual and broadcasting activities", 61 "Telecommunications" and 62-63 "IT and other information services". Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table B.2. Productivity growth and catch-up of laggards between: digital and knowledge intensity, lagged productivity gap

(a) Labour productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
LP gap	0.2222***	0.2102***	0.2079***	0.1865***	0.1924***	0.1897***	0.2000***	0.2217***
	(0.017)	(0.014)	(0.015)	(0.020)	(0.019)	(0.018)	(0.015)	(0.019)
LP gap × X	-0.0685**	-0.0423**	-0.0335***	-0.0318***	-0.0117*	-0.0304***	-0.0363***	-0.0781**
	(0.030)	(0.017)	(0.012)	(0.012)	(0.006)	(0.010)	(0.013)	(0.030)
Adj. R-Square	0.745	0.740	0.747	0.730	0.725	0.738	0.751	0.753
Observations	4852	4852	4852	4094	4852	4852	4852	2354
Num countries	13	13	13	13	13	13	13	13
LP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

(b) Multifactor productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
MFP gap	0.1745***	0.1557***	0.1543***	0.1336***	0.1393***	0.1361***	0.1496***	0.1829***
	(0.012)	(0.013)	(0.013)	(0.020)	(0.021)	(0.017)	(0.011)	(0.015)
MFP gap × X	-0.0815***	-0.0401***	-0.0316***	-0.0343***	-0.0190***	-0.0313***	-0.0403***	-0.0965***
	(0.024)	(0.015)	(0.009)	(0.008)	(0.005)	(0.008)	(0.010)	(0.024)
Adj. R-Square	0.490	0.474	0.485	0.461	0.460	0.475	0.498	0.497
Observations	4296	4296	4296	3566	4296	4296	4296	1908
Num countries	13	13	13	13	13	13	13	13
MFP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

Note: LP (MFP) growth top firms corresponds to LP (MFP) growth between *t-1* and *t* of firms in the top decile of the LP (MFP) distribution at time *t-1*. LP (MFP) gap is computed as the difference (at time t-3) between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). All variables *X* are standardized, except in columns (1) and (8) where *X* denotes dummy variables. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: $^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$.

Table B.3. Productivity growth and catch-up of laggards: digital and knowledge intensity, robustness to heterogeneous capital intensity

(a) Labour productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
LP gap	0.2234***	0.2062***	0.2070***	0.1968***	0.2053***	0.1973***	0.2017***	0.2241***
	(0.015)	(0.012)	(0.012)	(0.014)	(0.013)	(0.013)	(0.012)	(0.019)
LP gap × X	-0.0642**	-0.0478**	-0.0341***	-0.0273**	-0.0096	-0.0280***	-0.0347**	-0.0722**
	(0.030)	(0.019)	(0.012)	(0.011)	(0.006)	(0.010)	(0.013)	(0.030)
LP gap × K/L	0.0003	-0.0145	-0.0068	0.0099	0.0131	0.0063	-0.0007	0.0049
	(0.009)	(0.011)	(0.009)	(0.012)	(0.012)	(0.010)	(0.009)	(0.009)
Adj. R-Square	0.752	0.750	0.755	0.740	0.737	0.747	0.758	0.758
Observations	5946	5946	5946	4978	5946	5946	5946	2847
Num countries	13	13	13	13	13	13	13	13
LP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

(b) Multi-factor productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
MFP gap	0.1715***	0.1486***	0.1491***	0.1363***	0.1432***	0.1371***	0.1461***	0.1806***
	(0.013)	(0.013)	(0.013)	(0.016)	(0.016)	(0.015)	(0.012)	(0.016)
MFP gap × X	-0.0827***	-0.0592***	-0.0355***	-0.0321***	-0.0175***	-0.0307***	-0.0409***	-0.0960***
	(0.024)	(0.017)	(0.009)	(0.008)	(0.005)	(0.007)	(0.011)	(0.025)
MFP gap × K/L	-0.0065	-0.0284**	-0.0128	0.0052	0.0070	0.0021	-0.0063	-0.0053
	(0.010)	(0.013)	(0.011)	(0.014)	(0.014)	(0.012)	(0.010)	(0.012)
Adj. R-Square	0.491	0.485	0.489	0.462	0.461	0.476	0.499	0.494
Observations	5315	5315	5315	4386	5315	5315	5315	2340
Num countries	13	13	13	13	13	13	13	13
MFP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

Note: LP (MFP) growth top firms corresponds to LP (MFP) growth between *t-1* and *t* of firms in the top decile of the LP (MFP) distribution at time *t-1*. LP (MFP) gap is computed as the difference between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). All variables *X* are standardized, except in columns (1) and (8) where it denotes dummy variables. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: $^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$.

Table B.4. Productivity growth and catch-up of laggards: digital and knowledge intensity, within country-sector-quantile regressions

(a) Labour productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
LP gap	0.1281***	0.1056***	0.1070***	0.0879***	0.0936***	0.0935***	0.1023***	0.1215***
	(0.028)	(0.019)	(0.019)	(0.022)	(0.023)	(0.021)	(0.020)	(0.035)
LP gap × X	-0.0760**	-0.0389***	-0.0302***	-0.0281***	-0.0162**	-0.0286***	-0.0381**	-0.0855**
	(0.034)	(0.014)	(0.010)	(0.010)	(0.007)	(0.010)	(0.016)	(0.039)
Adj. R-Square	0.913	0.913	0.913	0.916	0.912	0.912	0.913	0.925
Observations	5933	5933	5933	4967	5933	5933	5933	2843
Num countries	13	13	13	13	13	13	13	13
LP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-sector-quantile year FE	yes	yes	yes	yes	yes	yes	yes	yes

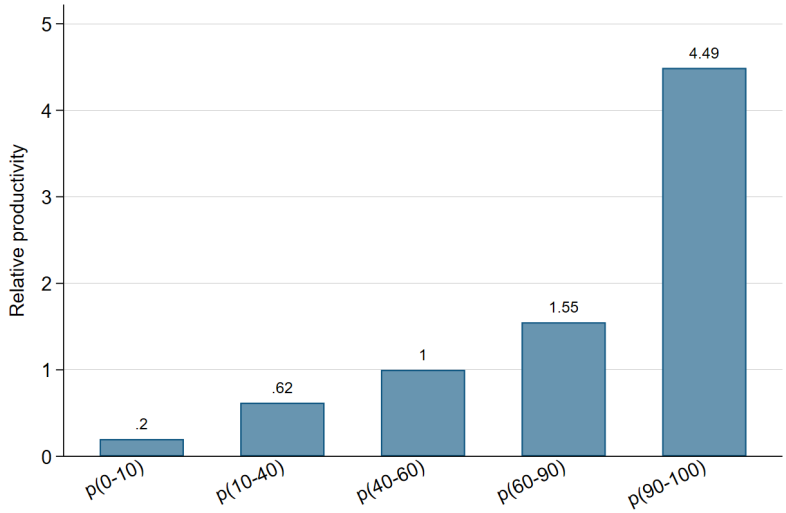
(b) Multi-factor productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
MFP gap	0.0818***	0.0621***	0.0615***	0.0558***	0.0589***	0.0580***	0.0649***	0.0578***
	(0.016)	(0.013)	(0.013)	(0.012)	(0.012)	(0.011)	(0.012)	(0.022)
MFP gap × X	-0.0507**	-0.0106	-0.0092	-0.0196	-0.0040	-0.0267**	-0.0267***	-0.0176
	(0.021)	(0.011)	(0.010)	(0.012)	(0.010)	(0.012)	(0.010)	(0.027)
Adj. R-Square	0.890	0.889	0.889	0.895	0.889	0.890	0.890	0.909
Observations	5300	5300	5300	4377	5300	5300	5300	2334
Num countries	13	13	13	13	13	13	13	13
MFP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-sector-quantile year FE	yes	yes	yes	yes	yes	yes	yes	yes

Note: LP (MFP) growth top firms corresponds to LP (MFP) growth between *t-1* and *t* of firms in the top decile of the LP (MFP) distribution at time *t-1*. LP (MFP) gap is computed as the difference between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). All variables *X* are standardized, except in columns (1) and (8) where it denotes dummy variables. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

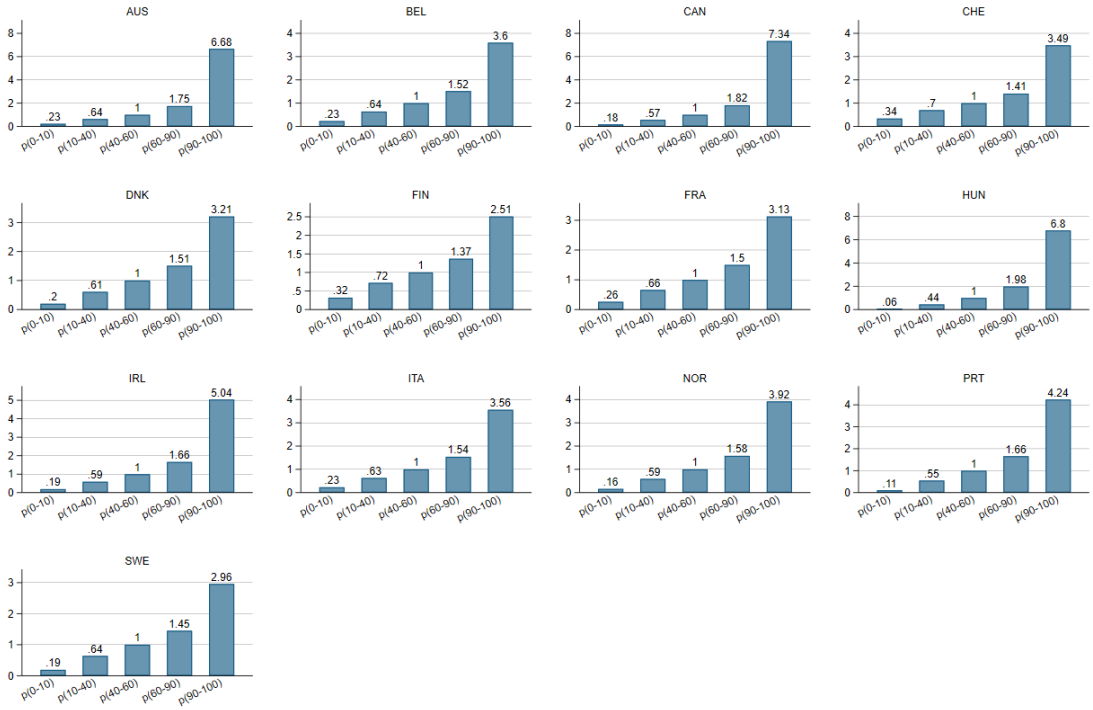
C. Additional Figures

Figure C.1. Average MFP by MFP group relative to the median



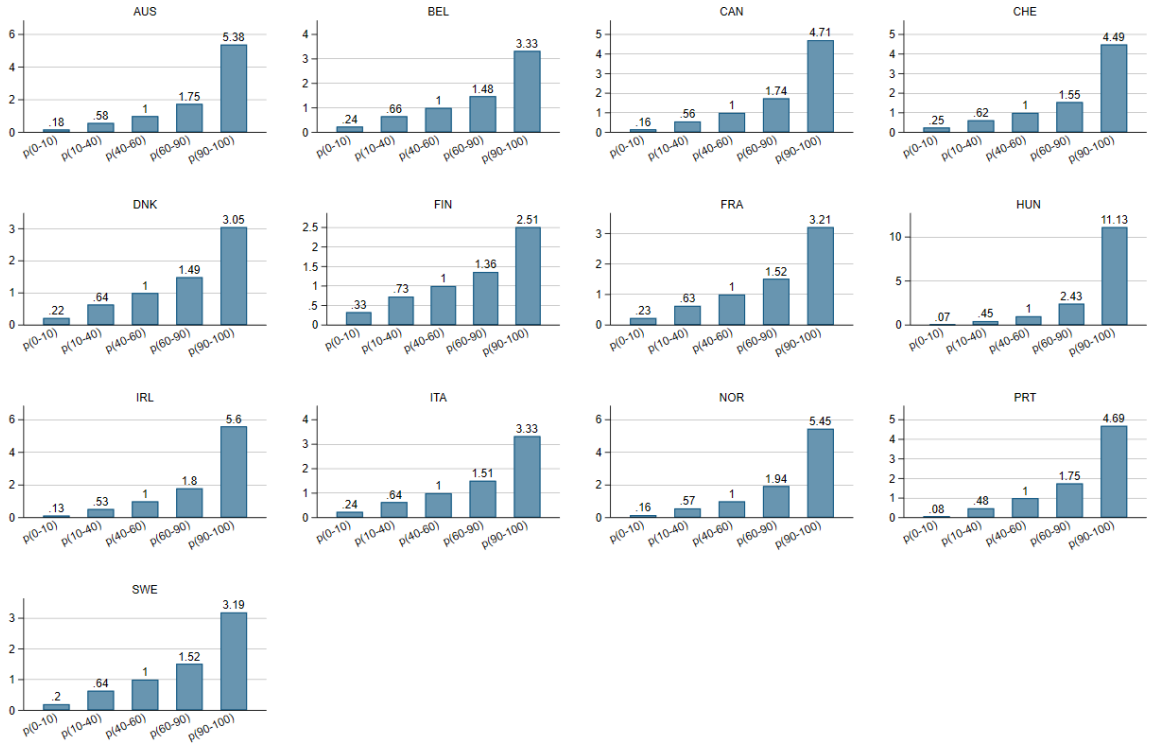
Note: The figure plots the weighted average multi-factor productivity in different groups of the productivity distribution with respect to the median group. In particular, the MFP distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE.

Figure C.2. Average LP by LP group relative to the median, by country



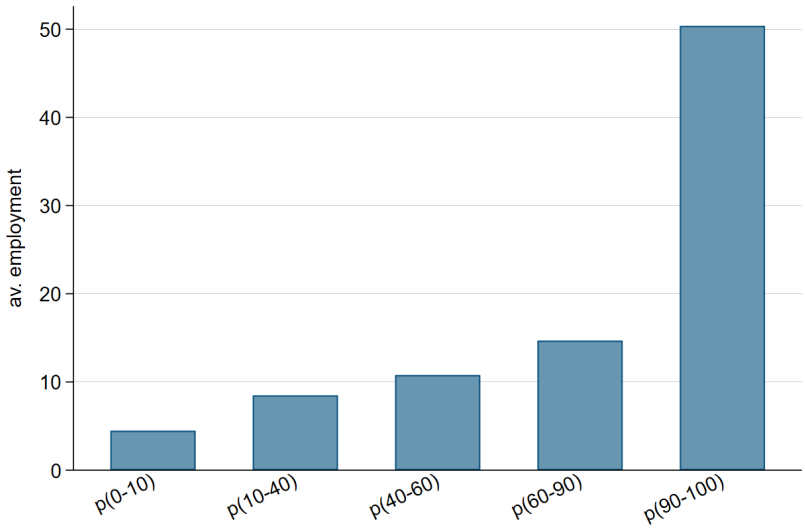
Note: The figure plots, for each country, the weighted average labour productivity in different groups of the productivity distribution with respect to the meadian group. In particular, the LP distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only.

Figure C.3. Average MFP by MFP group relative to the median, by country



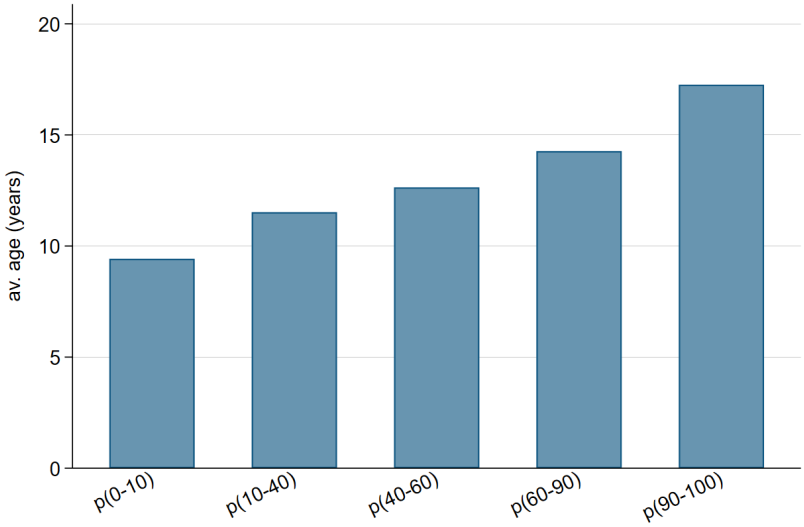
Note: The figure plots, for each country, the weighted average multi-factor productivity in different groups of the productivity distribution with respect to the meadian group. In particular, the MFP distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only.

Figure C.4. Average size by MFP group



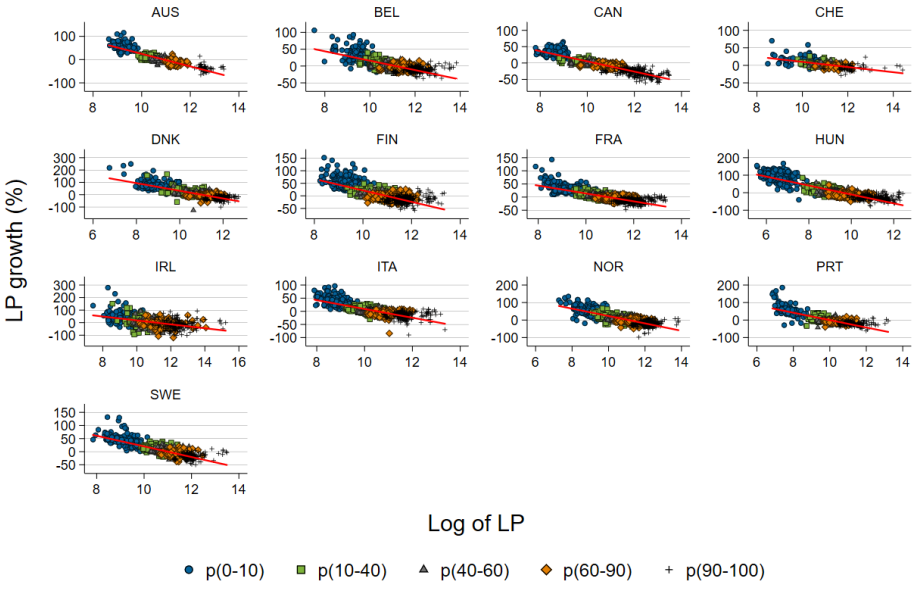
Note: The figure plots the average (employment) size in different groups of the productivity distribution. In particular, the MFP distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE.

Figure C.5. Average age by MFP group



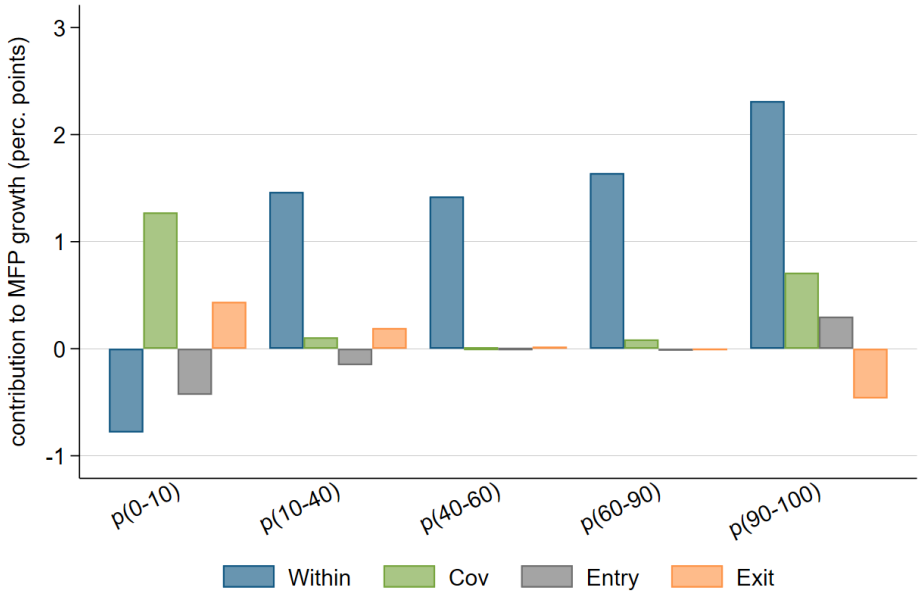
Note: The figure plots the average age in different groups of the productivity distribution. In particular, the MFP distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only. Countries included: BEL, DNK, FRA, IRL, ITA, NOR, SWE.

Figure C.6. Average LP and within firm LP growth, by country



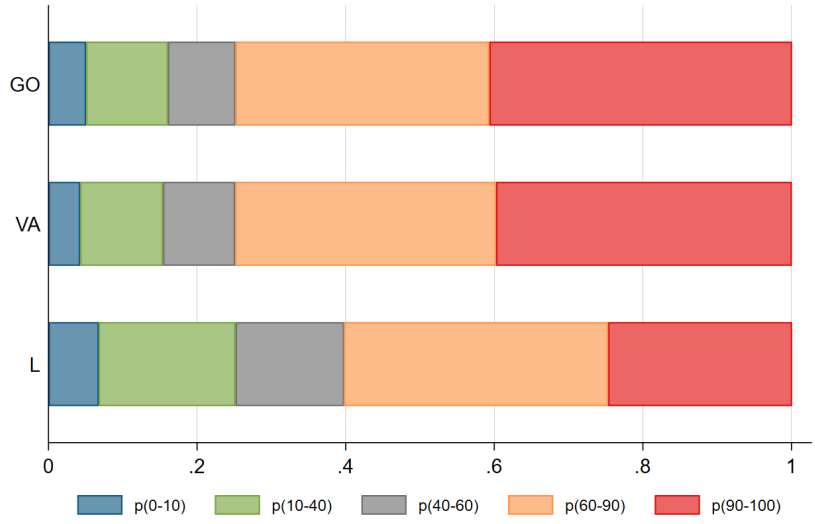
Note: The figure plots, for each country, the correlation between the average initial level of labour productivity at time *t* and the average firm-level productivity growth between *t* and *t+1*, within a country-industry-productivity group-year cell. The productivity distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only.

Figure C.7. Melitz and Polanec decomposition by MFP group



Note: The figure plots the Meliz and Polanec decomposition in different groups of the productivity distribution. In particular, the MFP distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. The bars of this figure are computed in the following way: first gains are aggregated across industries within country and productivity groups using employment shares of the industry in the economy. Subsequently, a simple average is computed across years within each country-productivity group. Finally, the median is computed over countries, separately for p(0-10) and p(10-40).

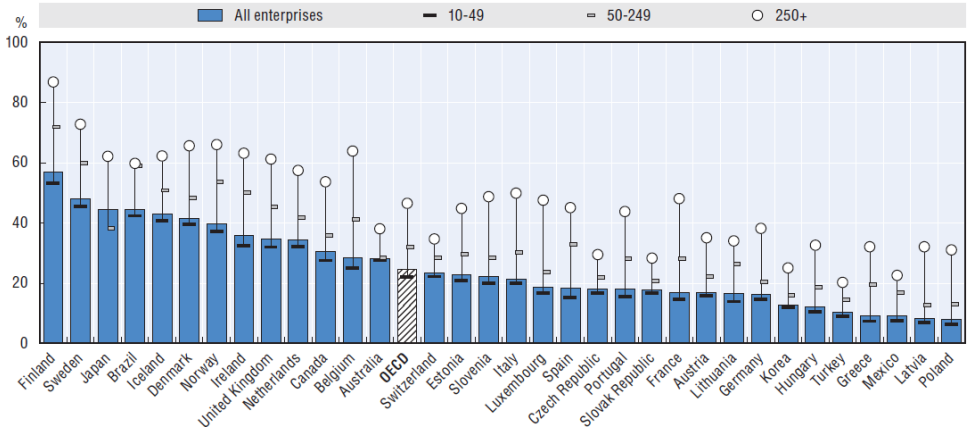
Figure C.8. Share of gross output, value added and employment by MFP group



Note: The figure plots the average share of gross output (GO), value added (VA) and employment (L) in each group of the productivity distribution. In particular, the MFP distribution has been split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE.

Figure C.9. Enterprises using cloud computing services, by firm size, 2016

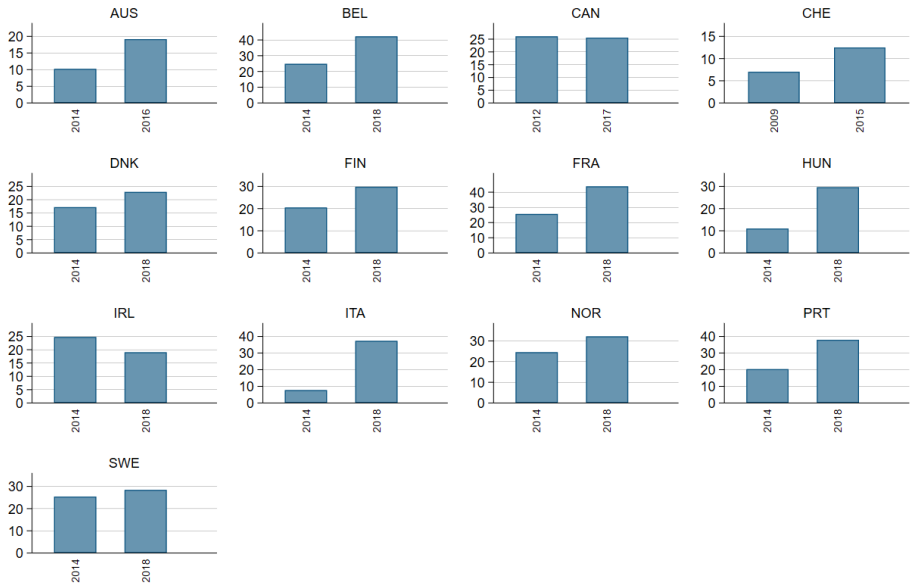
As a percentage of enterprises in each employment size class



Note: Cloud computing refers to ICT services used over the Internet as a set of computing resources to access software, computing power, storage capacity and so on. Data refer to manufacturing and non-financial market services enterprises with ten or more persons employed, unless otherwise stated. Size classes are defined as: small (10-49 persons employed), medium (50-249) and large (250 and more). OECD data are based on a simple average of the available countries.

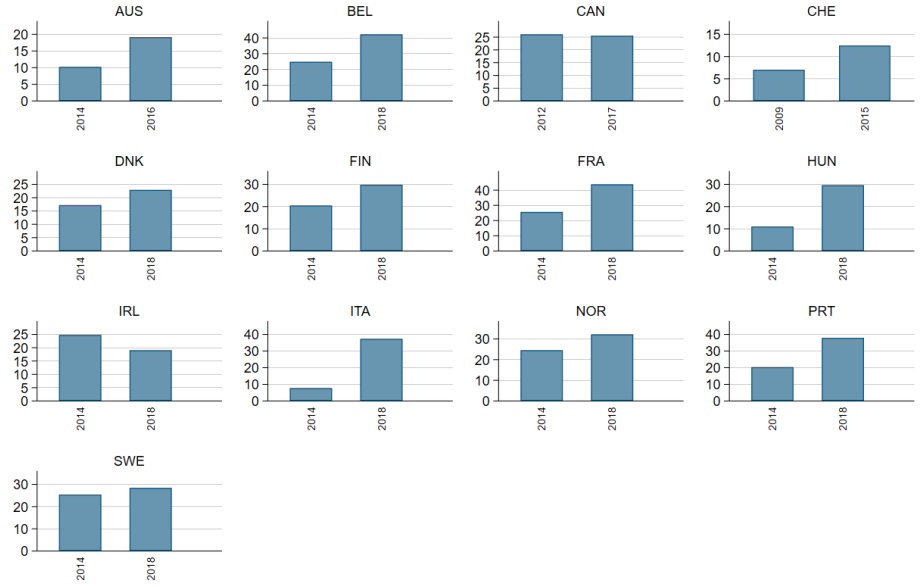
Source: OECD (2017).

Figure C.10. Difference between small and large firms in the use of cloud computing



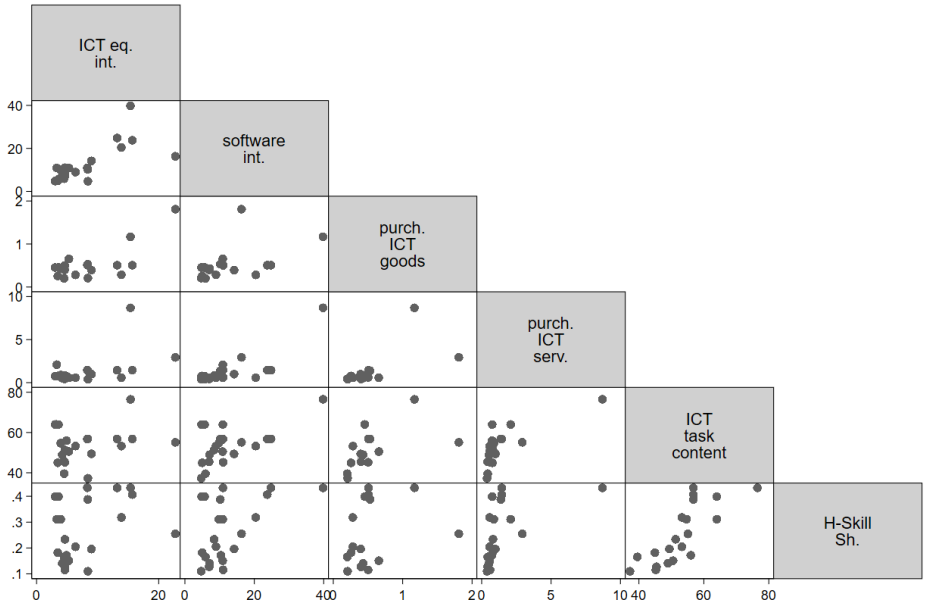
Note: The figure plots for each country the difference in the percentage of large firms (250 employees or more) and small firms (10 to 49 employees) purchasing cloud computing services. The difference is reported for the first and last year available.
Source: OECD ICT Access and Usage by Businesses database, accessed May 2019.

Figure C.11. Difference in access to high speed broadband between small and large firms



Note: The figure plots, for each country, the difference in the percentage of large firms (250 employees or more) and small firms (10 to 49 employees) with broadband download speed at least 100Mbit/s. The difference is reported for the first and last year available.
Source: OECD ICT Access and Usage by Businesses database, accessed May 2019.

Figure C.12. Correlation between different dimensions of digitalisation and knowledge intensity



Note: This matrix correlation graph illustrates the correlation between each pair of indicator of digital and knowledge intensity. Each column corresponds to a different variable X_j. The correlation between two variables X_i and X_k is illustrated by the scatter plot represented in column *i* row *k*.

D. Additional Tables

Table D.5. Employment and age distribution by LP group, manufacturing vs. non-financial market services

		Manufacturing			Market Services		
Productivity group	% Firms	Avg. Age	Avg. Firm size	% Empl.	Avg. Age	Avg. Firm size	% Empl.
Very bottom [p(0-10)]	10%	12.94	12.06	4.02	8.58	11.54	6.48
Bottom [p(10-40)]	30%	15.99	22.37	16.19	9.82	14.74	27.1
Median group [p(40-60)]	20%	17.39	38.97	16.51	11.06	18.56	21.17
Above the median [p(60-90)]	30%	18.14	70.21	41.11	11.7	26.42	34.23
National frontier [p(90-100)]	10%	17.4	93.68	22.17	11.86	39.68	11.01

Note: Numbers are averages across countries and years. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Due to censoring on the firm birth year variable in some countries, the table reports average age based on 6 countries only: BEL, DNK, FRA, IRL, ITA, NOR, SWE.

Table D.6. Age and size differences across productivity performance groups

	(1) Age	(2) Age	(3) Size	(4) Size
p(0-10)	-3.57***	-3.24***	-6.42***	-2.55***
	(0.368)	(0.290)	(1.307)	(0.667)
p(10-40)	-1.43***	-1.40***	-2.40	-2.13***
	(0.106)	(0.097)	(1.640)	(0.331)
p(60-90)	0.67***	1.46***	1.83*	7.31***
	(0.205)	(0.083)	(1.072)	(0.956)
p(90-100)	0.75	3.71***	1.64	50.49***
	(0.520)	(0.400)	(1.688)	(6.981)
Adj. R-Square	0.898	0.877	0.445	0.358
Observations	9414	9271	16499	16323
Nb. country	7	7	13	13
Country-Industry-Year FE	yes	yes	yes	yes
Productivity	LP	MFP	LP	MFP

Note: This table reports the results from a regression of average age (Columns 1 and 2) and size (Columns 3 and 4) on a categorical variable with values representing each productivity (LP in Columns 1 and 3, MFP in Columns 2 and 4) group, including country-2-digit industry-year fixed effects. The median group, p(40-60), is the reference category (the coefficient is therefore omitted). For other productivity groups, coefficients correspond to average differences in age or size within each country-2-digit industry-year with respect to the median group. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Due to censoring on the firm birth year variable in some countries, regressions based on average age include: BEL, DNK, FRA, IRL, ITA, NOR, SWE. Clustered standard errors at the country-sector level in parentheses: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table D.7. Share of gross output, value added and employment by LP group

Productivity bin	% Firms	% GO	% VA	% L
Very bottom [p(0-10)]	10%	1.45%	0.79%	4.94%
Bottom [p(10-40)]	30%	10.36%	10.36%	24.43%
Median group [p(40-60)]	20%	12.21%	12.84%	19.92%
Above the median [p(60-90)]	30%	38.65%	39.21%	37.88%
National frontier [p(90-100)]	10%	37.32%	36.80%	12.83%

The table reports the share of gross output (GO), value added (VA) and employment (L) in each group of the productivity distribution. In particular, the LP distribution is split into 5 groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE.

Table D.8. Share of gross output, value added and employment by MFP group

Productivity bin	% Firms	% GO	% VA	% L
Very bottom [p(0-10)]	10%	5.07%	4.28%	6.77%
Bottom [p(10-40)]	30%	11.02%	11.14%	18.42%
Median group [p(40-60)]	20%	9.08%	9.69%	14.60%
Above the median [p(60-90)]	30%	34.18%	35.14%	35.55%
National frontier [p(90-100)]	10%	40.72%	39.80%	24.75%

The table reports the share of gross output (GO), value added (VA) and employment (L) in each bin of the productivity distribution. In particular, the MFP distribution is split into 5 bins: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE.

Table D.9. Productivity growth and catch-up: digital and knowledge intensity, within country-sector-quantile regressions

(a) Labour productivity

	(1) Baseline (1)	(2) Baseline (2)	(3) Service dummy	(4) Av. age
LP gap	0.0648***	0.0876***	0.1171***	0.1129***
	(0.022)	(0.021)	(0.020)	(0.022)
LP gap × X			-0.0347	-0.0034*
			(0.028)	(0.002)
Adj. R-Square	0.899	0.912	0.912	0.891
Observations	5952	5933	5933	3495
Num countries	13	13	13	7
LP growth top firms	no	yes	yes	yes
country-sector-quantile year FE	yes	yes	yes	yes

(b) Multi-factor productivity

	(1) Baseline (1)	(2) Baseline (2)	(3) Service dummy	(4) Av. age
MFP gap	0.0360***	0.0587***	0.0628***	0.0667***
	(0.011)	(0.012)	(0.017)	(0.019)
MFP gap × X			-0.0052	-0.0018
			(0.021)	(0.001)
Adj. R-Square	0.869	0.889	0.889	0.885
Observations	5353	5300	5300	3185
Num countries	13	13	13	7
MFP growth top firms	no	yes	yes	yes
country-sector-quantile year FE	yes	yes	yes	yes

Note: LP (MFP) growth top firms corresponds to LP (MFP) growth between *t-1* and *t* of firms in the top decile of the LP (MFP) distribution at time *t-1*. LP (MFP) gap is computed as the difference between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table D.10. Slowdown in the speed of convergence

	(1) LP	(2) MFP
gap (baseline = 2000)	0.2809***	0.1906***
	(0.021)	(0.046)
gap× 2001	0.0030	-0.0412**
	(0.029)	(0.020)
gap× 2002	-0.0199	-0.0224
	(0.020)	(0.045)
gap× 2003	-0.0398*	-0.0472
	(0.022)	(0.045)
gap× 2004	-0.0185	-0.0070
	(0.023)	(0.046)
gap× 2005	-0.0256	-0.0357
	(0.023)	(0.033)
gap× 2006	-0.0189	-0.0738*
	(0.022)	(0.038)
gap× 2007	-0.0218	-0.1003**
	(0.026)	(0.049)
gap× 2008	0.0122	-0.0538
	(0.027)	(0.046)
gap× 2009	-0.0404	-0.1056**
	(0.026)	(0.050)
gap× 2010	-0.0402*	-0.1135**
	(0.022)	(0.046)
gap× 2011	-0.0479**	-0.0778
	(0.024)	(0.049)
gap× 2012	-0.0818**	-0.1008*
	(0.033)	(0.051)
Adj. R-Square	0.659	0.340
Observations	4984	4504
Num countries	13	13
country-year sector FE	yes	yes

Note: The productivity gap is computed as the difference between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). The first row of the table corresponds to the speed of catch-up in the baseline year, while the interaction of gap with each year dummy corresponds to the difference in the speed of convergence compared to the baseline year. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: $^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$.

Table D.11. Productivity growth and catch-up of laggards: digital and knowledge intensity

(a) Labour productivity

	(1) LP	(2) LP	(3) LP	(4) LP	(5) LP	(6) LP
LP gap	0.2100***	0.2139***	0.2188***	0.1880***	0.2062***	0.2144***
	(0.014)	(0.013)	(0.014)	(0.018)	(0.015)	(0.013)
LP gap × ICT eq. intensity	0.0058	-0.0429**				
	(0.019)	(0.021)				
LP gap × Software intensity	-0.0358**		-0.0527***		-0.0124	-0.0363*
	(0.015)		(0.019)		(0.012)	(0.019)
LP gap × ICT serv. intermeditate		0.0045	0.0298*	0.0336*		0.0248*
		(0.010)	(0.016)	(0.018)		(0.015)
LP gap × ICT goods intermediate						
LP gap × ICT task intensity				-0.0580**		
				(0.023)		
LP gap × H-SKill Sh.					-0.0248	-0.0162
					(0.018)	(0.017)
Adj. R-Square	0.755	0.749	0.762	0.754	0.759	0.764
Observations	5946	5946	5946	5946	5946	5946
Num countries	13	13	13	13	13	13
LP growth top firms	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes

(b) Multifactor productivity

	(1) MFP	(2) MFP	(3) MFP	(4) MFP	(5) MFP	(6) MFP
MFP gap	0.1541***	0.1551***	0.1572***	0.1333***	0.1516***	0.1519***
	(0.013)	(0.013)	(0.012)	(0.020)	(0.012)	(0.011)
MFP gap × ICT eq. intensity	0.0027	-0.0354*				
	(0.021)	(0.021)				
MFP gap × Software intensity	-0.0331***		-0.0400**		-0.0071	-0.0084
	(0.012)		(0.018)		(0.010)	(0.019)
MFP gap × ICT serv. intermeditate		-0.0062	0.0114	0.0122		0.0012
		(0.009)	(0.015)	(0.018)		(0.013)
MFP gap × ICT goods intermediate						
MFP gap × ICT task intensity				-0.0429*		
				(0.024)		
MFP gap × H-SKill Sh.					-0.0332**	-0.0326**
					(0.016)	(0.015)
Adj. R-Square	0.486	0.478	0.489	0.478	0.499	0.499
Observations	5315	5315	5315	5315	5315	5315
Num countries	13	13	13	13	13	13
MFP growth top firms	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes

Note: LP (MFP) growth top firms corresponds to LP (MFP) growth between *t-1* and *t* of firms in the top decile of the LP (MFP) distribution at time *t-1*. LP (MFP) gap is computed as the difference between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). All indicators of digital and skill intensity are standardized. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.12. Productivity growth and catch-up of laggards between t-5 and t: digital and knowledge intensity

(a) Labour productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
LP gap	0.0433***	0.0407***	0.0405***	0.0365***	0.0377***	0.0372***	0.0391***	0.0435***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
LP gap × X	-0.0129**	-0.0073*	-0.0058**	-0.0061***	-0.0025***	-0.0053***	-0.0064**	-0.0150**
	(0.006)	(0.004)	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)	(0.007)
Adj. R-Square	0.753	0.748	0.751	0.738	0.741	0.747	0.754	0.748
Observations	4040	4040	4040	3385	4040	4040	4040	1929
Num countries	12	12	12	12	12	12	12	12
LP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

(b) Multifactor productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
MFP gap	0.0373***	0.0340***	0.0337***	0.0289***	0.0303***	0.0296***	0.0323***	0.0405***
	(0.003)	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)
MFP gap × X	-0.0169***	-0.0090**	-0.0070***	-0.0073***	-0.0042***	-0.0065***	-0.0084***	-0.0227***
	(0.007)	(0.004)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.006)
Adj. R-Square	0.605	0.601	0.606	0.570	0.590	0.597	0.610	0.590
Observations	3586	3586	3586	2952	3586	3586	3586	1562
Num countries	12	12	12	12	12	12	12	12
MFP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

Note: LP (MFP) growth top firms corresponds to LP (MFP) growth between *t-5* and *t* of firms in the top decile of the LP (MFP) distribution at time *t-5*. LP (MFP) gap is computed as the difference (at time t-5) between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). All variables *X* (reported as title of columns) are standardized, except in columns (1) and (8) where *X* denotes dummy variables. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: $^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$.

Table D.13. Productivity growth and catch-up of laggards: digital and knowledge intensity, restricted sample (2005-onward)

(a) Labour productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
LP gap	0.1934***	0.2079***	0.2059***	0.1864***	0.1912***	0.1881***	0.1974***	0.1764***
	(0.017)	(0.014)	(0.015)	(0.020)	(0.019)	(0.019)	(0.016)	(0.019)
LP gap × X	-0.0313**	-0.0382**	-0.0315***	-0.0261**	-0.0088*	-0.0278***	-0.0346**	-0.0365**
	(0.015)	(0.017)	(0.012)	(0.010)	(0.005)	(0.011)	(0.014)	(0.016)
Adj. R-Square	0.749	0.745	0.751	0.735	0.731	0.742	0.755	0.757
Observations	3582	3582	3582	3008	3582	3582	3582	1717
Num countries	13	13	13	13	13	13	13	13
LP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

(b) Multi-factor productivity

	(1) Digital dummy	(2) ICT eq. intensity	(3) Software intensity	(4) ICT goods intermediate	(5) ICT serv. intermeditate	(6) ICT task intensity	(7) H-SKill Sh.	(8) KIS dummy
MFP gap	0.1390***	0.1503***	0.1472***	0.1260***	0.1312***	0.1287***	0.1443***	0.1244***
	(0.013)	(0.015)	(0.016)	(0.022)	(0.023)	(0.020)	(0.013)	(0.015)
MFP gap × X	-0.0406***	-0.0417***	-0.0313***	-0.0310***	-0.0167***	-0.0299***	-0.0416***	-0.0481***
	(0.012)	(0.016)	(0.010)	(0.008)	(0.005)	(0.009)	(0.011)	(0.013)
Adj. R-Square	0.478	0.461	0.468	0.441	0.441	0.457	0.486	0.481
Observations	3260	3260	3260	2698	3260	3260	3260	1468
Num countries	13	13	13	13	13	13	13	12
MFP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

Note: LP (MFP) growth top firms corresponds to LP (MFP) growth between *t-1* and *t* of firms in the top decile of the LP (MFP) distribution at time *t-1*. LP (MFP) gap is computed as the difference between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). All variables *X* (reported as titles of columns) are standardized, except in columns (1) and (8) where it denotes dummy variables. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table D.14. MFP dispersion and digital and knowledge intensity

	(1) MFP disp 90-10	(2) MFP disp 90-10	(3) MFP disp 90-10	(4) MFP disp 90-10	(5) MFP disp 90-10	(6) MFP disp 90-10	(7) MFP disp 90-10	(8) MFP disp 90-10
Digital	0.1452***							
	(0.047)							
ICT eq. int.		0.2013***						
		(0.032)						
software int.			0.0991***					
			(0.028)					
purch. ICT goods				0.0916**				
				(0.044)				
purch. ICT serv.					0.0586**			
					(0.027)			
ICT task content						0.0820***		
						(0.030)		
H-Skill Sh.							0.1007***	
							(0.029)	
KIS								0.1606**
								(0.068)
Constant	1.8068***	1.8066***	1.8318***	1.8780***	1.8505***	1.8805***	1.8728***	1.8650***
	(0.029)	(0.018)	(0.023)	(0.025)	(0.022)	(0.022)	(0.026)	(0.020)
Adj. R-Square	0.687	0.767	0.715	0.679	0.676	0.695	0.718	0.772
Observations	3639	3639	3639	2975	3639	3639	3639	1641
Num countries	13	13	13	13	13	13	13	13
country-year FE	yes	yes	yes	yes	yes	yes	yes	yes

Note: "MFP disp 90-10" is a measure of productivity dispersion computed as the difference between the 90^{th} and 10^{th} percentile of the log productivity distribution. Manufacturing and non-financial market services only. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.15. Productivity growth and catch-up of laggards, skills-related objectives and policies

(a) Labour productivity

	Sh. well macthed		Sh. underqual.		Training work. adults		ALMP training	
	(1) Digital dummy	(2) H-SKill Sh.	(3) Digital dummy	(4) H-SKill Sh.	(5) Digital dummy	(6) H-SKill Sh.	(7) Digital dummy	(8) H-SKill Sh.
LP gap	0.2369***	0.2257***	0.2304***	0.2227***	0.2099***	0.2100***	0.1999***	0.1916***
	(0.012)	(0.009)	(0.016)	(0.012)	(0.021)	(0.017)	(0.017)	(0.013)
LP gap × Ind	-0.0333**	-0.0178***	-0.0235	-0.0136*	0.0021	-0.0035	-0.0250	-0.0152*
	(0.015)	(0.006)	(0.018)	(0.007)	(0.024)	(0.010)	(0.021)	(0.009)
LP gap × Pol	0.0382***	0.0475***	-0.0267***	-0.0377***	0.0238**	0.0279***	0.0212**	0.0259***
	(0.009)	(0.007)	(0.008)	(0.007)	(0.010)	(0.008)	(0.009)	(0.007)
LP gap × Pol × Ind	0.0187*	0.0099**	-0.0239**	-0.0113**	0.0131	0.0080	0.0254	0.0139*
	(0.011)	(0.005)	(0.011)	(0.005)	(0.015)	(0.007)	(0.016)	(0.008)
Pol × Ind	-0.0271	-0.0212**	0.0424*	0.0247**	-0.0032	-0.0047	-0.0194	-0.0106
	(0.023)	(0.010)	(0.022)	(0.010)	(0.024)	(0.011)	(0.027)	(0.012)
Adj. R-Square	0.853	0.854	0.842	0.843	0.834	0.836	0.788	0.795
Observations	4886	4886	4886	4886	4856	4856	5361	5361
Num countries	11	11	11	11	11	11	13	13
LP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

(b) Multifactor productivity

	Sh. well macthed		Sh. underqual.		Training work. adults		ALMP training	
	(1) Digital dummy	(2) H-SKill Sh.	(3) Digital dummy	(4) H-SKill Sh.	(5) Digital dummy	(6) H-SKill Sh.	(7) Digital dummy	(8) H-SKill Sh.
MFP gap	0.1723***	0.1714***	0.1680***	0.1664***	0.1653***	0.1626***	0.1654***	0.1524***
	(0.015)	(0.015)	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)	(0.013)
MFP gap × Ind	-0.0087	-0.0021	-0.0110	-0.0029	-0.0072	-0.0022	-0.0456**	-0.0182**
	(0.022)	(0.010)	(0.023)	(0.010)	(0.026)	(0.011)	(0.019)	(0.008)
MFP gap × Pol	0.0134*	0.0235***	-0.0134	-0.0163**	0.0100	0.0166	0.0174	0.0259*
	(0.008)	(0.007)	(0.008)	(0.008)	(0.014)	(0.014)	(0.015)	(0.013)
MFP gap × Pol × Ind	0.0218**	0.0069	-0.0034	0.0021	0.0173	0.0069	0.0363*	0.0239**
	(0.010)	(0.005)	(0.012)	(0.007)	(0.023)	(0.010)	(0.021)	(0.009)
Pol × Ind	-0.0807***	-0.0340***	0.0263	0.0084	-0.0410	-0.0158	-0.0760*	-0.0457**
	(0.024)	(0.013)	(0.027)	(0.014)	(0.046)	(0.020)	(0.043)	(0.019)
Adj. R-Square	0.598	0.604	0.591	0.598	0.589	0.589	0.515	0.526
Observations	4249	4249	4249	4249	4248	4248	4876	4876
Num countries	11	11	11	11	11	11	13	13
MFP growth top firms	yes	yes	yes	yes	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes	yes	yes	yes	yes

Note: LP (MFP) growth top firms corresponds to LP (MFP) growth between *t-1* and *t* of firms in the top decile of the LP (MFP) distribution at time *t-1*. LP (MFP) gap is computed as the difference between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). All variables *Pol* (titles of columns groups) are standardized and the variable *Ind* is standardized when it corresponds to the share of high-skilled workers ("H-Skill Sh"). Manufacturing and non-financial market services only. All regressions also include the interaction between the productivity gap and GDP/capita in *t-1*. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table D.16. Productivity growth and catch-up of laggards: the role of financial conditions

(a) Labour productivity

	Spread large-small		sh. loans SMEs	
	(1) ICT eq. intensity	(2) Software intensity	(3) ICT eq. intensity	(4) Software intensity
LP gap	0.1801***	0.1782***	0.2028***	0.2014***
	(0.013)	(0.013)	(0.011)	(0.011)
LP gap × Ind	-0.0283***	-0.0220***	-0.0272***	-0.0257***
	(0.010)	(0.007)	(0.007)	(0.006)
LP gap × Pol	0.0026	0.0017	0.0285***	0.0341***
	(0.006)	(0.006)	(0.010)	(0.010)
LP gap × Pol × Ind	-0.0125***	-0.0076*	0.0329***	0.0176***
	(0.005)	(0.004)	(0.007)	(0.006)
Pol × Ind	0.0214**	0.0106	-0.0530***	-0.0246**
	(0.010)	(0.009)	(0.017)	(0.012)
Adj. R-Square	0.767	0.771	0.831	0.834
Observations	2428	2428	2064	2064
Num countries	12	12	10	10
LP growth top firms	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes

(b) Multifactor productivity

	Spread large-small		sh. loans SMEs	
	(1) ICT eq. intensity	(2) Software intensity	(3) ICT eq. intensity	(4) Software intensity
MFP gap	0.1342***	0.1353***	0.1483***	0.1396***
	(0.012)	(0.012)	(0.015)	(0.015)
MFP gap × Ind	-0.0145	-0.0062	-0.0255***	-0.0123
	(0.012)	(0.009)	(0.009)	(0.008)
MFP gap × Pol	0.0072	0.0072	-0.0029	0.0026
	(0.006)	(0.007)	(0.010)	(0.011)
MFP gap × Pol × Ind	-0.0209***	-0.0151**	0.0529***	0.0334***
	(0.005)	(0.006)	(0.008)	(0.008)
Pol × Ind	0.0387***	0.0211	-0.1323***	-0.0820***
	(0.014)	(0.014)	(0.020)	(0.021)
Adj. R-Square	0.514	0.528	0.554	0.541
Observations	2365	2365	1836	1836
Num countries	11	11	9	9
MFP growth top firms	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes

Note: LP (MFP) growth top firms corresponds to LP (MFP) growth between *t-1* and *t* of firms in the top decile of the LP (MFP) distribution at time *t-1*. LP (MFP) gap is computed as the difference between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). All variables *Pol* (titles of columns groups) and variables *Ind* (titles of columns) are standardized. Manufacturing and non-financial market services only. All regressions also include the interaction between the productivity gap and GDP/capita in *t-1*. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.17. Productivity growth and catch-up of laggards: government funding of business R&D

(a) Labour productivity

	BERD financed by gov (%GDP)		BERD financed by gov (%BERD)	
	(1) Digital dummy	(2) H-SKill Sh.	(3) Digital dummy	(4) H-SKill Sh.
LP gap	0.2003***	0.1824***	0.2023***	0.1837***
	(0.012)	(0.010)	(0.013)	(0.011)
LP gap × Ind	-0.0586***	-0.0310***	-0.0576***	-0.0318***
	(0.017)	(0.007)	(0.017)	(0.007)
LP gap × Pol	-0.0093	-0.0083	-0.0052	0.0021
	(0.007)	(0.005)	(0.007)	(0.006)
LP gap × Pol × Ind	0.0136	0.0067	0.0282***	0.0118***
	(0.011)	(0.004)	(0.009)	(0.004)
Pol × Ind	-0.0275	-0.0090	-0.0611***	-0.0221***
	(0.020)	(0.008)	(0.018)	(0.008)
Adj. R-Square	0.797	0.806	0.801	0.807
Observations	4496	4496	4565	4565
Num countries	12	12	12	12
LP growth top firms	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes

(b) Multifactor productivity

	BERD financed by gov (%GDP)		BERD financed by gov (%BERD)	
	(1) Digital dummy	(2) H-SKill Sh.	(3) Digital dummy	(4) H-SKill Sh.
MFP gap	0.1660***	0.1548***	0.1651***	0.1535***
	(0.015)	(0.011)	(0.015)	(0.011)
MFP gap × Ind	-0.0588***	-0.0274***	-0.0577***	-0.0268***
	(0.017)	(0.007)	(0.016)	(0.007)
MFP gap × Pol	-0.0136	-0.0078	-0.0062	-0.0009
	(0.009)	(0.007)	(0.010)	(0.008)
MFP gap × Pol × Ind	0.0294***	0.0194***	0.0288**	0.0200***
	(0.011)	(0.005)	(0.013)	(0.006)
Pol × Ind	-0.0487*	-0.0300***	-0.0463*	-0.0310**
	(0.026)	(0.011)	(0.027)	(0.012)
Adj. R-Square	0.523	0.551	0.519	0.541
Observations	4032	4032	4102	4102
Num countries	12	12	12	12
MFP growth top firms	yes	yes	yes	yes
country-year sector FE	yes	yes	yes	yes

Note: LP (MFP) growth top firms corresponds to LP (MFP) growth between *t-1* and *t* of firms in the top decile of the LP (MFP) distribution at time *t-1*. LP (MFP) gap is computed as the difference between log productivity at the frontier (top 10% most productive firms in the same country, industry, year) and firms in the two groups of laggards, p(0-10) and p(10-40). All variables *Pol* (titles of columns groups) are standardized and the variable *Ind* is standardized when it corresponds to the share of high-skilled workers ("H-Skill Sh"). Manufacturing and non-financial market services only. All regressions also include the interaction between the productivity gap and GDP/capita in *t-1*. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, SWE. Clustered standard errors at the country-sector level in parentheses: $^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$.