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LAST BUT NOT LEAST: LAGGARD FIRMS, TECHNOLOGY DIFFUSION, AND ITS STRUCTURAL AND POLICY DETERMINANTS*

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Using a unique microaggregated data set on firm-level productivity in 13 countries from 1995 to 2014, this article provides new evidence on technology- and knowledge-diffusion barriers for laggard firms. We show that, although the least productive firms benefit from a catch-up effect, their speed of catchup is lower in digital- and skill-intensive industries. This is especially true in countries with high skill mismatch, high financing frictions, and low absorptive capacity. These barriers to diffusion, combined with the rising importance of tacit knowledge and intangibles, could help explain the productivity growth slowdown observed in the last decades.

1. INTRODUCTION

Over the last decades, productivity growth has been disappointingly slow despite potential efficiency gains in production and innovation expected from the progress in information and communication technologies (ICTs, e.g., Fernald, 2015; Gordon, 2016; Syverson, 2017). A prominent explanation of this apparent paradox hinges on the fact that ICTs are general-purpose technologies characterized by an S-curve of adoption and diffusion: time is needed for new technologies to convert into productivity gains (see Jovanovic and Rousseau, 2005, for a review). Implementation lags would therefore be at the root of the "modern productivity paradox" (Brynjolfsson et al., 2017).

Several barriers are also likely to hamper a broad and rapid diffusion of technology and productive knowledge, particularly digital technologies and intangible assets. Their adoption and absorption require sizeable investments not only in newly developed technologies, but also in complementary intangible assets, and modified business processes and work practices (e.g., Haskel and Westlake, 2017). Such barriers may slow down the diffusion process (Akcigit and Ates, 2023, 2021) and induce a technological divergence between frontier firms and the rest (e.g., Andrews et al., 2016; Decker et al., 2020). In addition, productivity divergence is more pronounced at the bottom of the distribution, potentially suggesting a more severe slowdown in the diffusion of knowledge to the least productive firms (Berlingieri et al., 2024).

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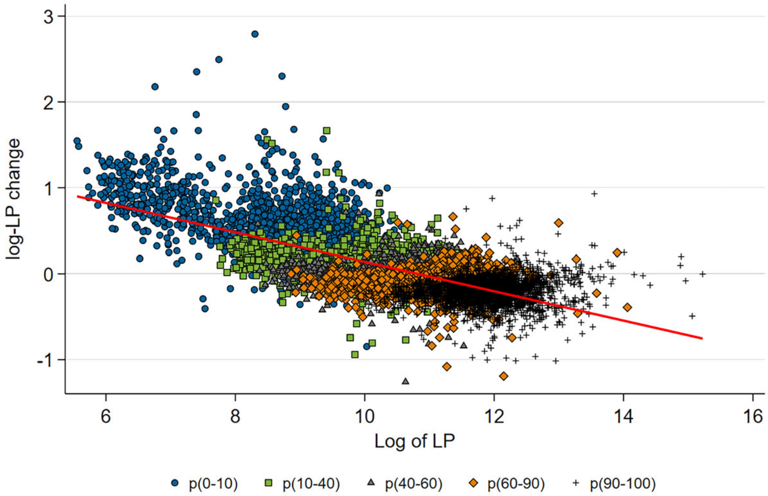

NOTES: The figure illustrates the correlation between the average initial level of labor productivity at time $t-1$ and the average firm-level productivity growth between $t-1$ and t, within a country–industry–productivity group-year cell. The productivity distribution is split into five groups: 1st to 10th percentile, 10th to 40th, 40th to 60th, 60th to 90th, and 90th to 100th. Data are for manufacturing and nonfinancial market services. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, and SWE.

FIGURE 1

AVERAGE LABOR PRODUCTIVITY AND WITHIN FIRM LABOR PRODUCTIVITY GROWTH

Using a unique data set that collects microaggregated firm-level information on productivity in 13 countries from 1995 to 2014, this article provides new evidence on technology- and knowledge-diffusion barriers for laggard firms. We focus on the left tail of the productivity distribution because barriers to technology diffusion from frontier to laggard firms—particularly those related to the digital and knowledge economy—are important to understand ongoing productivity trends. Although laggards contribute little to aggregate productivity from a static perspective, their contribution to productivity growth and economic dynamism remains crucial for long-term economic growth. Figure 1 shows a negative correlation between firms' average initial labor productivity (LP) and average productivity growth. It suggests that lower productivity is associated with faster subsequent growth, especially at the very bottom of the distribution where firms are smaller and younger than the rest, as our data show.

This evidence can be rationalized by a neo-Schumpeterian growth model (e.g., Acemoglu et al., 2006; Aghion and Howitt, 2006) that predicts (conditional) productivity convergence: laggard firms should grow faster, given the larger stock of unexploited technologies and knowledge that they can readily implement to enhance production efficiency. Following Griffith et al. (2004), we present a theoretical framework in line with this class of models where the convergence process is affected by the absorptive capacity of firms. In this framework, laggard firms find it more challenging to catch up whenever the required ability to assimilate, transform, and use knowledge is higher, that is, when the required level of absorptive capacity is higher. Indeed, laggard firms might not be able to sustain high levels of investment or to access the advanced skills needed to succeed in a knowledge-intensive sector. Furthermore, a lower speed of catchup results in a higher level of productivity dispersion, reflecting the slower diffusion of innovation.

In our empirical investigation, we find that the national frontier indeed exerts a strong pull on the bottom of the distribution, as in Bartelsman et al. (2008). The strength of the pull from the frontier is heterogeneous across firms and sectors, in line with the role of absorptive capacity highlighted by Griffith et al. (2004).[1] More specifically, using several (time-invariant)

[1] Griffith et al. (2004) show that firms investing more intensively in R&D develop their absorptive capacity and therefore catch up faster.

measures of digital and knowledge intensity, we show that laggard firms in more digital- and knowledge-intensive industries display lower catch-up rates. This finding is further corroborated by the fact that more digital- and knowledge-intensive industries also display higher levels of productivity dispersion, as predicted by the theoretical framework that guides our empirical strategy. The combination of these results suggests that digital technologies and intangible assets do not diffuse immediately, possibly due to higher barriers to their adoption and efficient usage, which are particular severe for laggard (possibly young) firms. This slower diffusion, in turn, translates into higher firm heterogeneity in industries that rely more heavily on digital technologies and knowledge, whereby the required level of absorptive capacity is higher.

We then provide additional evidence that the slower catchup in these industries may indeed reflect barriers to diffusion. More specifically, we focus on three types of barriers: skill mismatch, financing frictions, and lack of absorptive capacity. We find that the negative correlation between the speed of catchup and industries' digital and knowledge intensity is generally stronger in countries where these barriers are higher. First, the negative correlation between digital/skill intensity and the speed of catchup is stronger in countries with a higher mismatch between workers' education level and the level required for their jobs. Second, tighter financial conditions for small and medium-sized enterprises (SMEs), as indicated by a higher interest rate spread between large and small firms, are also linked to a higher negative correlation between digital/knowledge intensity and catchup. Conversely, an economic environment supporting laggards' absorptive capacity through more generous (direct) public funding of business expenditures on R&D seems to be associated with a higher speed of catchup in digital- and skill-intensive industries.

Our article relates and contributes to several strands of the literature. Using unique data from the OECD MultiProd project, which collects microaggregated statistics representative of the entire population of firms across several OECD countries and two-digit industries, we investigate the strength of the diffusion process focusing on the left tail of the productivity distribution. These laggard firms, defined as firms belonging to the bottom 40% of the productivity distribution, are rarely studied due to the lack of representative data, especially in a cross-country setting. In general, laggards could be described as: (i) low-productivity firms that would typically exit in a competitive market, such as "zombie firms" (e.g., Caballero et al., 2008; McGowan et al., 2018); (ii) SMEs that, by the nature of their governance, are likely to remain small and have a limited scope for productivity growth (e.g., local services, family businesses); (iii) firms experiencing a temporary productivity shock; and (iv) firms entering the economy, which are likely to operate below their productivity potential during the first stage of their development.[2], [3] Our analysis offers evidence in favor of the last point and suggests that firms in the left tail have the potential to grow and are key to economic dynamism, in contrast with the view that low-productivity firms are mostly zombies dragging productivity growth due to weak market selection and misallocation. Our results indeed show that laggard firms are younger and display higher productivity growth rates than the rest.

These characteristics are consistent with the prediction of models of firm dynamics, learning, and selection (e.g., Jovanovic, 1982; Hopenhayn, 1992; Ericson and Pakes, 1995; Melitz, 2003). Following these models, firms may learn their productivity only after entering the market and either quickly exit, if they are of the low-productivity type, or stay and expand. As

[2] However, note that not all young low-productivity firms operate below their efficiency scale, as some of them are just experimenting and quickly exiting the market. Foster et al. (2008, 2016) show that it might also reflect the fact that start-ups need to build reputation, that is, a lack of intangible assets, such as brand reputation instead of technological efficiency.

[3] 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-based multi-factor productivity and the overestimation of their output price. Firm-specific prices are indeed usually unobserved, so industry-wide price deflators are used. 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 may underestimate the entrants' physical output and, consequently, productivity.

already mentioned, the fact that less productive firms grow faster is also in line with the (conditional) productivity convergence predicted by the neo-Schumpeterian growth theory (e.g., Acemoglu et al., 2006; Aghion and Howitt, 2006) and by models of competitive diffusion (e.g., Jovanovic and MacDonald, 1994). Moreover, this evidence is in line with well-established results showing that despite their initially negative contribution to aggregate productivity growth (e.g., Hyytinen and Maliranta, 2013; Melitz and Polanec, 2015), new and young firms are an important source of employment growth (e.g., Haltiwanger et al., 2013; Criscuolo et al., 2014; Criscuolo et al., 2017) and productivity growth (Decker et al., 2017). They contribute to innovation and the process of creative destruction, and exert a positive competition effect on leaders' innovation (e.g., Aghion et al., 2001, 2009; Klenow and Li, 2020).

Furthermore, we provide novel evidence that the diffusion of technology and knowledge has been lower in more digital- and knowledge-intensive industries and that overall diffusion has slowed down over time. A slow diffusion of technology and knowledge could have significant consequences for economies. Akcigit and Ates (2021, 2023) find that a decline in knowledge diffusion is the most powerful force driving some much-debated economic macro trends, including slow productivity growth, rising productivity dispersion, rising market concentration and markups, declining business dynamism (i.e., slowing down job reallocation, declining entry rates, and decreasing share of young firms in economic activity), as well as declining labor shares. Indeed, a slowdown in diffusion from frontier firms to laggards endogenously leads to lower innovation incentives and thereby reduces aggregate productivity growth through: (i) a direct discouragement effect that reduces the investment incentives of laggard firms; and (ii) an indirect diminishing escape competition effect for leaders, which reduces their incentives to innovate and maintain their technological advantage and position in the market. We provide direct evidence on the discouragement effect for laggard firms, which is particularly severe in digital- and knowledge-intensive industries.

Finally, De Ridder (2024) finds that differences in the adoption of intangible assets can explain the slowdown in productivity growth, as well as the decline in business dynamism and the rise of market power. Andrews et al. (2016) also find evidence that the pace of diffusion has slowed down over time and suggest that this "breakdown of the diffusion machine" is related to the digital transformation and the large adjustment costs associated with it. Moreover, recent studies find that the decline in business dynamism is more pronounced in digital-intensive and high-tech sectors (Decker et al., 2016; Calvino and Criscuolo, 2019; Bijnens and Konings, 2020; Calvino et al., 2020), whereas markups, productivity dispersion, and market concentration are higher in digital- and intangible-intensive sectors (Calligaris et al., 2018; Bessen, 2020; Bajgar et al., 2021; Corrado et al., 2021; McMahon et al., 2021). Our results dovetail previous findings in the literature and offer direct evidence on the barriers to knowledge diffusion that hinder the catchup of laggard firms.

The rest of the article is organized as follows: Section 2 presents a theoretical framework to evaluate convergence forces triggered by a catch-up effect. Section 3 describes our data, our measures of productivity and of digital intensity, and provides descriptive statistics. Section 4 presents our empirical framework and the main results of the article on catchup as a driver of convergence, its heterogeneity across sectors, as well as the existence of possible barriers to diffusion. Section 5 assesses the robustness of the main results and presents an additional investigation of how the catch-up rate evolves over time. Finally, Section 6 concludes.

2. THEORETICAL FRAMEWORK

In this section, we outline the theoretical framework that underlies the catch-up equations based on the neo-Schumpetarian growth model presented in Griffith et al. (2004), and provides a link between the speed of diffusion and productivity dispersion.[4]

[4] See the working paper version (Griffith et al., 2000) for a complete derivation of the framework based on a model of endogenous innovation and growth.

There is a conventional output production function in which value-added (VA) Y is produced according to a standard neoclassical production technology which combines productivity and physical input(s):

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

where output Y, productivity A, and inputs Z are allowed to vary across countries c, industries j, time t, and our unit of observation q. Since we will exploit cross-country microaggregated data in the empirical analysis (see Section 3), our unit of observation is a productivity performance group (e.g., the bottom decile) and not an individual firm. If $\mathcal{F}(\cdot) = \mathcal{F}(L_{cjq,t})$, A then represents LP. If instead $\mathcal{F}(\cdot) = \mathcal{F}(L_{cjq,t}, K_{cjq,t})$, differences in capital intensity are accounted for, and A represents multifactor productivity (MFP). In the latter case, $\mathcal{F}$ is assumed 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 defined as the national frontier ($q = F$).

The model presented follows the empirical literature on R&D and productivity growth (see, e.g., Griliches and Lichtenberg, 1984; Griffith et al., 2004), and in particular relies on the model proposed by Griffith et al. (2004), 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 article, we assume that productivity is primarily a function of technology or knowledge, $G_{cjq,t}$, and of other determinants, $B_{cjq,t}$, for instance, capturing knowledge diffusion. So $A_{cjq,t} = \mathcal{H}(G_{cjq,t}, B_{cjq,t})$.[5] Thanks to the assumption of separability between technology and other factors of production in Equation (1), and assuming a small rate of depreciation of the technology/knowledge stock, the rate of (labor or multifactor) productivity growth can be written as:[6]

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

where $\rho_{cjq,t}$ is the rate of return or marginal product of technology/knowledge ($\partial Y_{cjq,t}/\partial G_{cjq,t}$) and $\nu_{cjq,t}$ is the elasticity of output with respect to the other determinants of productivity growth ($\partial Y_{cjq,t}/\partial B_{cjq,t} \cdot B_{cjq,t}/Y_{cjq,t}$). $X = I/Y$ indicates the technology/knowledge intensity of the sector where I stands for real investment in technology.

In line with the empirical implementation below, we further assume that technology/knowledge intensity is a characteristic of the industry shared by all productivity performance groups q. We take this assumption for two main reasons: (i) there are no existing data sources that report technological indicators by performance group in a cross-country cross-industry framework, as we point out in Subsection 3.4; (ii) it alleviates potential endogeneity concerns that technology investment might be jointly determined with productivity. In anticipation of our empirical strategy and to reinforce the point mentioned in item (ii) above, we adopt country and time-invariant measures of technology and knowledge intensity. Our objective is to capture industry-specific structural characteristics related to their exposure to digital technologies. The equation above then becomes:

$$\Delta \ln A_{cjq,t} = \rho_{cjq,t}X_j + \nu_{cjq,t}\Delta \ln B_{cjq,t}. \tag{3}$$

To analyze more systematically the link between productivity growth and the gap in productivity across firms, we rely on the framework presented by Griffith et al. (2004). In this framework, the country-level productivity growth at time t is assumed to be a function of its lagged productivity gap with the frontier of productivity in $t-1$ (catch-up effect), and the

[5] As discussed in Section 3, our measure of productivity may also be related to demand-side factors and market structure.

[6] See Appendix A in the Online Appendix for the details of the derivation.

contemporaneous rate of productivity growth of the frontier itself 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, in order to account for spillovers and catch-up effects, the set of additional factors influencing productivity, B, includes productivity growth at the national frontier and the productivity gap with the national frontier:

$$\Delta \ln B_{cjq,t} = \pi_{cjq,t} \Delta \ln A_{cjF,t} + \sigma_{cjq,t} \ln \left(\frac{A_F}{A_q} \right)_{cj,t-1} + u_{cjq,t}, \tag{4}$$

where $\ln (A_F/A_q)_{cj,t-1}$ 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 nonfrontier productivity group is below the level at the frontier, $\ln (A_F/A_q)_{cj,t-1}$ is positive. The higher $\ln (A_F/A_q)_{cj,t-1}$, the further firms in performance group q lie behind the technological frontier in the same industry, and the greater the potential for technology transfer and knowledge spillovers.

Plugging (4) into (3) yields an expression for the evolution of productivity in performance group q relative to the national frontier F:

$$\Delta \ln A_{cjq,t} = \lambda_{cjq,t} \Delta \ln A_{cjF,t} + \beta_{cjq,t} \ln \left(\frac{A_F}{A_q} \right)_{cj,t-1} + \rho_{cjq,t} X_j + u_{cjq,t}, \tag{5}$$

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

In Equation (5), the analyzed technology/knowledge, 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., 2004) have emphasized the importance of absorptive capacity, that is, a firm's ability to identify, assimilate, transform, and use knowledge, research, and practices that exist outside the firm itself. To allow for technology transfer to be related to the absorptive capacity of firms, Equation (5) 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 nonfrontier performance groups is allowed to be a function of X:

$$\beta_{cjq,t} = \beta_1 + \beta_2 X_j. \tag{6}$$

Note that the previous literature has stressed the role of the technical competence and skills of agents in the adopting country or industry to facilitate technology transfers. In this article, we investigate the role of technological/knowledge intensity of the industry firms belong to. We are therefore a priori agnostic about the sign of the coefficient β_2. However, a high level of technological intensity implies that laggard (potentially young) firms need to sustain high levels of investment to reach the technological level of their sector, or they need advanced skills to succeed in a knowledge-intensive sector. In technology- or knowledge-intensive sectors, laggard firms are expected to require higher absorptive capacity, making it more challenging for them to catch up. We therefore expect the sign of β_2 to be negative.

Substituting (6) into (5), we obtain our preferred model:

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

where, with respect to (5), a common coefficient on λ, β, and ρ has been imposed.

Finally, we can derive a steady-state relationship between productivity dispersion and the rate of technology diffusion. Following Griffith et al. (2000), there is no potential for technological transfer at the frontier and its productivity growth is given by

$$\Delta \ln A_{cjF,t} = \psi_{cjF} + \rho X_j + u_{cjF,t}, \tag{8}$$

where ψ_{cjF} captures differences across country and industries.

Therefore,

$$\Delta \ln\left(\frac{A_{cjq}}{A_{cjF}}\right)_t = \lambda \Delta \ln A_{cjF,t} + \beta_1 \ln\left(\frac{A_F}{A_q}\right)_{cj,t-1} + \beta_2 \ln\left(\frac{A_F}{A_q}\right)_{cj,t-1} \times X_j - \psi_{cjF} + \xi_{cjq,t}. \tag{9}$$

At the steady state, we assume that variables grow at a constant rate and that a positive gap in the productivity level between frontier and laggard firms persists in equilibrium (i.e., the productivity distribution has a positive spread). Under these assumptions, $\Delta \ln A_{cjq,t} = \Delta \ln A_{cjF,t} = \Delta \ln A^*_{cjF}$, and $\Delta \ln A_{cjq,t}/A_{cjF,t} = 0$. Thus, from the previous equation, we get

$$\ln\left(\frac{A_{cjF}}{A_{cjq}}\right)^* = \frac{\psi_{cjF} - \lambda \Delta \ln A^*_{cjF}}{\beta_1 + \beta_2 X_j} = \frac{(1-\lambda)\psi_{cjF} - \lambda \rho X_j}{\beta_1 + \beta_2 X_j}. \tag{10}$$

This expression shows a negative relationship between the level of productivity dispersion and the speed of catchup, $\beta_1 + \beta_2 X_j$, which are both positive.[7] Moreover, if $\beta_2 < 0$, this also implies a positive relationship between X_j and productivity dispersion.

3. DATA

This section provides an overview of our data, presents the main measures of productivity used, and provides our definition of laggard firms. It then discusses the measures of digital and skill intensity used in the analysis.

3.1. *The MultiProd Data Set: Cross-Country Harmonized and Representative Data on Productivity.* Our analysis relies on harmonized and representative cross-country data on productivity from the OECD MultiProd project, which analyzes the microdrivers of aggregate productivity growth. Although the availability of confidential microlevel data has expanded considerably for individual countries over the past decades, confidentiality concerns and other administrative issues still pose serious obstacles to the transnational access to official microdata. To circumvent these obstacles, the MultiProd project relies on a standardized routine that microaggregates confidential firm-level administrative data, via a *distributed microdata analysis*. Such decentralized method consists in collecting statistical moments of the distribution of firm characteristics (employment, productivity, wages, age, etc.) by a centrally written, but locally executed, routine that is flexible and automated enough to run across different data sources in different countries. The advantages of this data collection methodology are manifold. It puts a lower burden on national statistical agencies and limits running costs for such endeavors. Importantly, it directly uses national microlevel representative databases, while at the same time achieving a high degree of harmonization and comparability across countries, sectors, and over time. This methodology was pioneered in the early 2000s in a series of cross-country projects on firm demographics and productivity (Bartelsman et al., 2005, 2009).[8]

[7] Note that we find small estimates for the coefficient λ in our empirical analysis, which supports the assumption of a positive spread in the productivity distribution in equilibrium, that is, $(1-\lambda)\psi_{cjF} - \lambda\rho X_j > 0$.

[8] This study relies on the version 1.1 of the MultiProd database (March 2019). The OECD currently follows this approach in several ongoing projects, including MultiProd, DynEmp, and MicroBeRD. MultiProd, DynEmp, and

Table 1
YEARS COVERED IN THE MULTIPROD DATA SET

Country	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Australia								●	●	●	●	●	●	●	●	●	●	●		
Belgium						●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
Canada							●	●	●	●	●	●	●	●	●	●	●	●		
Denmark						●	●	●	●	●	●	●	●	●	●	●	●	●		
Finland	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●		
France	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●		
Hungary				●	●	●	●	●	●	●	●	●	●	●	●	●	●	●		
Ireland												●	●	●	●	●	●	●	●	●
Italy							●	●	●	●	●	●	●	●	●	●	●	●	●	●
Norway	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●		
Portugal										●	●	●	●	●	●	●	●	●		
Sweden								●	●	●	●	●	●	●	●	●	●	●		
Switzerland															●	●	●	●		

The primary source of data for the MultiProd database is administrative data covering the universe or near-universe of businesses with positive employment. For the countries in which administrative data on the full population of firms do not exist, the program relies on production surveys combined with a business register. The former contain all the variables needed for the analysis of productivity but may be limited to a sample of firms; the latter contains a more limited set of variables (mainly employment, sector of activity, age, and ownership) but for the entire population of firms. In such cases, business registers are used to construct variable-specific weights to reweight the data contained in the production surveys in order to construct microaggregated data that are as representative as possible for the whole population of firms, and hence comparable across countries.[9]

MultiProd collects data for all sectors of the economy, whenever available. For the purpose of this analysis, the sample is restricted to two-digit industries within manufacturing and nonfinancial market services. In addition, in order to guarantee the comparability across deciles of the productivity distribution and across macrosectors, the sample is further restricted to countries providing productivity statistics for both manufacturing and nonfinancial market services, and not imposing any threshold for including firms in the sampling frame. This last aspect is particularly relevant for the purpose of this article. 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: Australia, Belgium, Canada, Denmark, Finland, France, Hungary, Ireland, Italy, Norway, Portugal, Sweden, and Switzerland. Table 1 details the time coverage for each country.

The statistics collected in the MultiProd database are computed at various levels of aggregation and using different breakdowns. This article is based on statistics aggregated at the two-digit industry level (following the SNA A38 classification, see Table C.4 for further details) and further decomposed into five groups of firms corresponding to different productivity quantiles. In particular, the productivity distribution is 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).

MicroBeRD are projects carried forward by the Directorate for Science, Technology and Innovation (STI) at the OECD. The DynEmp project provides harmonized microaggregated data to analyze 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).

[9] Three countries rely on this ex post reweighting strategy: Australia, Ireland, and Italy. See also Berlingieri et al. (2017) for additional details on the MultiProd project and the methodology, Desnoyers-James et al. (2019) for information on the underlying data sources, and Bajgar et al. (2019) for further details about the representativeness of the MultiProd data set, as well as a comparison with the STAN data set.

This particular breakdown of the data is the main source of information for this article, and enables us to characterize more precisely firms with different levels of productivity and study their dynamics.

3.2. *Measures of Productivity.* The article relies on two measures of productivity, LP and 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 labor input. It is computed at the firm level as the (real) VA per worker:

$$\text{LP\_VA}_{it} = \frac{VA_{it}}{L_{it}}, \tag{11}$$

where VA_{it} is the value added of firm i at time t, and L_{it} is its employment.[10] The advantage of this measure is that it is widely available, less prone to measurement error, and requires no assumption on the production function (and can be easily aggregated into sector-level or country-level LP using employment weights). However, it does not account for the impact of other inputs, such as physical capital.

To properly address this issue and provide a more robust analysis, we also exploit a measure of MFP. MFP not only accounts for labor but also for capital inputs. Specifically, we estimate MFP at the firm level using the Wooldridge (2009) control function approach with VA as a measure of output and two inputs. Firms are assumed to have a Cobb–Douglas production function, but not necessarily constant returns to scale:

$$Y_{it} = A_{it} K_{it}^{\beta_K} L_{it}^{\beta_L}, \tag{12}$$

where A_{it}, firm i's MFP at time t, is typically unobserved and has to be estimated, and β_K and β_L vary at the industry (two-digit in our case) level. 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.[11]

In this article, we focus on revenue productivity, implying that we analyze the catch-up process from a broad perspective, and that our results may reflect several underlying mechanisms on which we are agnostic. The literature has indeed emphasized the role of physical efficiency, improved quality, product appeal, scale, or possibly market power for revenue productivity (e.g., Foster et al., 2008; De Loecker, 2011; Foster et al., 2016; Forlani et al., 2023). Although technological catchup is more closely related to the adoption of new technologies and the organization of production, the digital transformation, and the rising importance of intangibles has further reinforced the complementarity between physical efficiency, demand-side factors, and market structure. In this context, laggards may face additional barriers to the adoption and efficient use of new technologies and of knowledge to innovate and increase product quality. At the same time, descriptive statistics presented next reveal that laggards

[10] For the sake of maximizing cross-country comparability, we rely on head counts (HC) for measuring labor input, since it is the one most commonly available in the countries considered. We use full time equivalents (FTEs) instead when HC is not available.

[11] For a detailed discussion on control function approaches, see Ackerberg et al. (2007, 2015). As standard in the literature, we estimate the production functions at a relatively high level of aggregation (two digits). Although dispersion in the productivity measures may in part reflect heterogeneity in elasticities within an industry, this approach ensures the stability of the estimates, which are sensitive to small samples and outliers when estimating high-order polynomials (see Decker et al., 2020; Blackwood et al., 2021). Studies adopting a control function approach at a more detailed level typically focus on a single large country and on a subset of manufacturing industries (e.g., Blackwood et al., 2021). Given the cross-country nature of our study and our focus on the entire economy, we are limited in our ability to adopt a more granular approach.

TABLE 2
DESCRIPTIVE STATISTICS BY LP QUANTILES

Productivity group	Relative LP	Avg. Age	Avg. Size	% Empl.	% GO	% VA	Avg. Δ LogLP
Very bottom [p(0–10)]	0.21	10.4	6.4	4.7	1.4	0.7	0.38
Bottom [p(10–40)]	0.64	12.4	12.1	24.8	10.3	10.9	0.09
Median group [p(40–60)]	1	13.7	19	20.1	12.9	14	−0.01
Above the median [p(60–90)]	1.52	14.6	27.1	37.9	38.8	39.8	−0.07
National frontier [p(90–100)]	3.33	14.4	26.1	11.9	35.6	33.7	−0.18

NOTE: Numbers presented in the table correspond to the median of the underlying variables (see titles of columns) across countries, industries and years. Data are for manufacturing and nonfinancial market services. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, and SWE. Due to censoring on the firm birth year variable in some countries, the table reports average age based on seven countries only: BEL, DNK, FRA, IRL, ITA, NOR, and SWE.

are younger, smaller, and have low market shares, suggesting that markups are likely to play a marginal role in driving the results on productivity growth of laggards.[12]

As already mentioned, the data set is split into five productivity groups, based on 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 groups is constrained by confidentiality requirements, which impose a minimum number of observations in a cell (which is detailed at the country, two-digit industry, year, and productivity group level). Although this might impose some restriction on the definition of laggard firms, this predefined split allows us to work with a clear and harmonized definition of laggards across countries. It also balances the risk of data suppression due to confidentiality requirements and the level of information available.

3.3. *Laggard Firms: Definition and Descriptive Statistics.* Most of the recent literature studying the productivity puzzle and the increased dispersion in productivity has focused on "frontier" firms, defined, for instance, as the top 5% of firms with the highest productivity (e.g., Andrews et al., 2016; and Haldane, 2017 for the United Kingdom), as opposed to the "rest," defined as firms outside the frontier group. Very little is known about firms that operate at the (very) bottom of the productivity distribution, and their growth performance over time. In this article, we focus on the left tail of the productivity distribution, the so-called "laggards," that is, firms with low productivity relative to other firms in a given country–industry–year.

We define laggard firms as the 40% least productive firms in a given country–industry–year, considering both LP and MFP separately. We further distinguish two different groups of laggards: (i) 1st to 10th, and (ii) 10th to 40th percentiles of the productivity distribution (labeled p(0–10) and p(10–40), respectively). This is possible thanks to the richness and uniqueness of the MultiProd data set that includes moments drawn from firm-level data covering the universe or near-universe of firms, which are therefore representative of all parts of the productivity distribution. As such, the MultiProd data set is particularly suitable to analyze the bottom part of the productivity distribution, and allows us to focus on a more specific and targeted definition of laggard firms.

Tables 2 and 3 display, for each productivity group (for LP and MFP, respectively), summary statistics on: the productivity of firms in each productivity group relative to the median; firms' average age and employment size; the share of each group in total employment, gross

[12] Andrews et al. (2016) find a decline in catchup over time for a measure of MFP purged from markups. De Loecker et al. (2020) find that the secular increase in aggregate markups documented is driven mostly by firms in the upper tail of the distribution. In addition, Fitzgerald et al. (2024) show that in successful episodes of market entry there are dynamics of quantities, but no postentry dynamics of markups, suggesting that shifts in demand play an important role in successful entry, but that firms do not use dynamic manipulation of markups as an instrument to shift demand. Using data on consumer goods in the United States, Hottman et al. (2016) find that changes in markups play almost no role in explaining firm growth, especially for smaller firms.

TABLE 3
DESCRIPTIVE STATISTICS BY MFP QUANTILES

Productivity Group	Relative MFP	Avg. Age	Avg. Size	% Empl.	% GO	% VA	Avg. Δ LogMFP
Very bottom [p(0–10)]	0.19	10.6	5	3.2	1.1	0.5	0.35
Bottom [p(10–40)]	0.61	12.1	8.8	14.7	6.4	6.1	0.07
Median group [p(40–60)]	1	13.4	12.8	14.4	8.1	9	−0.01
Above the median [p(60–90)]	1.58	14.7	25.6	33	30.3	32.6	−0.06
National frontier [p(90–100)]	3.39	16.1	57.2	24.1	48.9	46.2	−0.14

NOTE: Numbers presented in the table correspond to the median of the underlying variables (see titles of columns) across countries, industries, and years. Data are for manufacturing and nonfinancial market services. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, and SWE. Due to censoring on the firm birth year variable in some countries, the table reports average age based on seven countries only: BEL, DNK, FRA, IRL, ITA, NOR, and SWE.

output (GO), and VA; and, the average within-firm productivity growth. These tables highlight noteworthy differences across firms with different levels of productivity. First, we find significant productivity gaps, in line with evidence from the literature (e.g., Syverson, 2011). Comparing laggards to the median group (firms in the p(40–60) group), we find that the average productivity of firms belonging to the bottom 10% of the distribution is one-fifth the average productivity of the median group. Firms belonging to the p(10–40) group exhibit an average productivity which is roughly 60% that of firms belonging to the median group. Second, firms' average number of employees increases with productivity, indicating that more productive firms are on average bigger in terms of employment. Accordingly, firms in higher productivity quantiles represent a higher share of total employment, GO, and VA. Third, firms in the bottom part of the distribution are younger than in the rest of the productivity distribution. Stated differently, the bottom half of the productivity distribution includes firms that are smaller and younger than the average, but that still represents a significant share of total employment: the 40% of firms with the lowest LP account for almost 30% of employment on average in manufacturing and nonfinancial market services, albeit less than 12% of GO and VA. Finally, as expected, productivity growth is decreasing with the productivity group, with the laggard groups displaying a positive average within-firm productivity growth, and firms belonging to the median or above the median groups displaying instead a negative productivity growth.[13], [14], [15]

3.4. *Measuring Digital and Knowledge Intensity.* Measuring digitalization is challenging for two main reasons: i) it is a multi-faceted phenomenon, and ii) there are significant limitations to the availability of data in a cross-country cross-industry framework and over time. To circumvent the first issue, we use six indicators of digital intensity capturing different facets of digitalization, and two indicators of knowledge (skill) intensity. All of them, described below, vary at the two-digit industry level, but are country and time-invariant. These measures aim at

[13] See also Tables C.1 and C.2 in the Online Appendix, which distinguish between manufacturing and nonfinancial market services. From these tables, it can be seen that services firms are generally younger and smaller than manufacturing ones. In addition, whereas in manufacturing productivity increases significantly with firm size, this is less the case in services. Berlingieri et al. (2018) also show that this relationship does not necessarily hold for services.

[14] Ardanaz-Badia et al. (2017) find similar characteristics of laggards in Great Britain over the period 2003–15: among firms in the bottom 10% of the LP distribution, roughly 93% of businesses in the United Kingdom had fewer than 10 employees, and 44% were aged one to five years (and an additional 20% were no more than 10 years old), highlighting that young and microfirms are overrepresented among the 10% least productive firms.

[15] For both LP and MFP, we also unveil a positive correlation between age and productivity on the one hand, and between size and productivity on the other hand, using a regression framework which focuses on the variation within country–industry–year. More specifically, we regress the average age and size of firms in a cell (country–industry–year–productivity group) on productivity group dummies while controlling for country–industry–year fixed effects. The estimates capture the average difference in terms of size and age for a given productivity performance group with respect to the median group (the reference category). Results in Online Appendix (C.3) confirm that laggards are on average younger and smaller when compared to more productive firms in the same country, industry, and year.

capturing industry-specific structural characteristics in terms of their exposure to digital technology as well as their need for a highly skilled or highly specialized labor force (Table C.4 in the Appendix for the classification of industries into digital-intensive and less digital-intensive categories).

We first rely on a dummy variable that distinguishes digital-intensive and nondigital-intensive industries (*measure 1*) based on the global taxonomy developed by Calvino et al. (2018), which encompasses many facets of digitalization, including its technological components (tangible and intangible ICT investment, purchases of intermediate ICT goods and services, and robots), the human capital it requires to embed technology in production (ICT specialists intensity), and the way it changes the interface of firms with the output market (online sales).[16]

Then, we also use individual indicators underlying the global taxonomy, focusing on the technological aspect of digitalization with four indicators: (i) investment intensity in ICT equipment (*measure 2*); (ii) investment intensity in software and database (*measure 3*); (iii) ICT goods as intermediate inputs (*measure 4*); and (iv) ICT services as intermediate inputs (*measure 5*).[17] Measures of investment intensity in ICT equipment (computer hardware and telecommunication equipment) *(measure 2)*, and software and databases *(measure 3)* take into account investments in both tangible and intangible ICT capital, respectively.[18] We also use two additional measures based on the use of ICT as intermediate inputs. Measures of ICT investment intensity (measures 2 and 3) indeed do not entirely account for the use of digital technologies in the production process, given that accounting rules recommend the capitalization 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, and data processing) and are therefore not counted in measures of ICT investment.[19] For this reason, we complement the analysis with indicators of the use of ICT goods *(measure 4)* and services *(measure 5)* as intermediate inputs. Purchases of ICT intermediate goods and services (measures 4 and 5) are based on the OECD Inter-Country Input–Output (ICIO) database, and are both normalized by real output.[20]

Note that these measures are cross-country averages of the underlying data for the period 2001–3 in each industry, that is, they are measured at the industry level and are time-invariant. Consequently, these indicators do not capture existing heterogeneity in the use of digital technologies across countries in the same industries, as well as changes over time, but are likely to capture structural industry characteristics regarding the scope for the use of digital technologies.

In addition, we consider the human capital dimension of the digital transformation to account for the fact that penetration of digital technologies is transforming occupations and the skills needed by workers to perform their job. To this aim, we use a measure of ICT task intensity *(measure 6)* from Grundke et al. (2017) and Calvino et al. (2018). This measure is based on data from the OECD Programme for the International Assessment of Adult Competencies (PIAAC), which provides information on the frequency with which surveyed

[16] Digital industries are those that are in the top quarter of digital intensity distribution of industries in either 2001–3 or 2013–15. See Calvino et al. (2018) for additional details.

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

[18] *Measure 2* is based on investment in ICT equipment as a percentage of total gross fixed capital formation (GFCF). *Measure 3* is based on purchases of software and databases also as percentage of GFCF.

[19] However, such expenses could be particularly relevant to take into account 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.

[20] For the machinery production sectors (ISIC revision 3 sectors 29–35), purchases of ICT intermediate goods are set to missing. They are indeed 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 "substitute" or "complementary" to investment.

individuals carry out tasks that are related to the use of ICT on the job.[21] 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.[22]

Finally, we use two measures of skill intensity as indicators of the knowledge intensity of sectors. The first measure is based on industry-level skill intensity computed as the share of hours worked by high-skill workers *(measure 7)*.[23] In this article, the skill intensity of each industry is computed as the average over the period 1995–99 for the United States. We also use a second measure of knowledge intensity that focuses on services. We construct a dummy variable that divides nonfinancial market services into knowledge-intensive services (KIS) and less knowledge-intensive services (LKIS) *(measure 8)*. This index relies on the Eurostat classification of KIS, which is based on the share of tertiary educated persons at the NACE Rev.2 two-digit level.[24]

3.5. *Measuring Barriers to Technology and Knowledge Diffusion.* To proxy potential barriers to technology and knowledge diffusion, we focus on factors related to human capital, financial conditions, and firms' absorptive capacity, particularly for laggards. We rely on cross-country, time-varying data on skill mismatch, the cost of external finance for SMEs, and government direct funding for business R&D, with the latter acting as an enabler of diffusion. These were sourced from OECD databases.

First, the skill mismatch measure is obtained from the OECD's World Indicators of Skills for Employment (WISE) database, specifically using the "Skills for Jobs" Indicators. Skill mismatch occurs when workers possess a level of education that is either higher or lower than what is required for their job (qualification mismatch). The mismatch index represents the proportion of workers in each country who are either over- or underqualified for their roles. This is calculated by comparing workers' educational attainment to the modal educational level required for each occupation, by country and time period.

Second, we use data on interest rate spreads between loans to large firms and SMEs, sourced from the OECD Scoreboard on Financing SMEs and Entrepreneurs. The idea is to proxy differential financial conditions across firms, especially between more productive larger firms and less productive smaller ones. This spread, measured in percentage points, reflects the cost difference between loans to SMEs and loans to large firms, providing insight into credit conditions for SMEs.

Finally, direct government support for business R&D is measured by government-financed business expenditures on R&D, expressed as a percentage of GDP. This measure is available from the OECD's R&D Tax Incentive Indicators.

4. EMPIRICAL FRAMEWORK AND MAIN RESULTS

The theoretical framework in Section 2 suggests that the diffusion of technology results in a positive correlation between firms' productivity gap and their productivity growth—conditional on their survival. Empirical studies have confirmed the existence of this catch-up effect both at the firm level (Bartelsman et al., 2008; Griffith et al., 2009; Andrews et al., 2015,

[21] The occupational based measure is translated into an industry measure of ICT task intensity using the weight of different occupations in each industry.

[22] 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 (2001-3) and relative digital intensity at the end of the period (20–2014). 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 partly reflects the relative ICT task intensity in the earlier period.

[23] 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 (Timmer et al., 2015).

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

2016) and at the industry level (Nicoletti and Scarpetta, 2003; Saia et al., 2015). The existence of a catch-up effect for laggard firms is a necessary condition for them to exit the group of low-productivity firms.

In this article, we exploit the richness of the MultiProd database, which combines the benefits of a microaggregated approach with the generality of a cross-country framework, to test the existence of a catch-up effect for laggard firms —the 40% least productive firms—to the national frontier in the same industry, and to explore factors related to the strength of this effect.

We first provide evidence that the catch-up effect related to knowledge and technology diffusion is a robust source of productivity growth for laggards. However, the speed of catchup is lower in digital- and knowledge-intensive industries, resulting in higher levels of productivity dispersion. We then show that the negative correlation between catchup and digital/skill intensity is stronger in countries where barriers to diffusion are more likely to be prevalent. Finally, we provide an additional investigation on the strength of the catch-up rate over time, which suggests that productivity convergence has declined over time.

4.1. *Heterogeneity in the Speed of CatchUp.* The first step of our empirical analysis is to confirm the existence of the neo-Schumpetarian catch-up effect at the bottom of the productivity distribution, and to evaluate factors related to the strength of this catch-up effect.

4.1.1. *Empirical framework.* The starting point of our econometric analysis is the convergence equation (7) derived in the theoretical framework. In general, productivity growth can also be affected by macroeconomic shocks at the country level and by industry characteristics, possibly correlated with the explanatory variables. To control for them, the error term in (7) is allowed to include country–year and industry fixed effects:

$$u_{cjq,t} = \delta_{ct} + \tau_j + \varepsilon_{cjq,t}. \tag{13}$$

Therefore, we estimate the following baseline equation to assess the strength of the catch-up effect, which we allow to vary according to different possible sources of heterogeneity:

$$\overline{\Delta P}_{cjq,t} = \alpha + \beta_1 gap_{cjq,t-1} + \beta_2 (gap_{cjq,t-1} \times X_j) + \lambda \overline{\Delta P}^F_{cj,t} + \delta_{ct} + \tau_j + \varepsilon_{cjq,t}. \tag{14}$$

We estimate this equation focusing on laggard firms, that is, the "left tail" of the productivity distribution, using the bottom productivity groups available in our data (p(0–10) and p(10–40)). $\overline{P}_{cjq,t}$ denotes the average firm (log) productivity (LP or MFP) in country c, two-digit industry j, productivity group q, and year t. $\overline{\Delta P}_{cjq,t}$ is the average within-firm annual (log) productivity growth (from time $t-1$ to t) of surviving firms belonging to the bottom 40% of the productivity distribution at time $t-1$, whereas $\overline{\Delta P}^F_{cj,t}$ is the average annual (log) productivity growth of firms at the national frontier, defined as the top 10% of the productivity distribution in each country, two-digit industry, and year. Moreover, $gap_{cjq,t-1}$ is the productivity gap at time $t-1$, modeled as the (absolute value of) the difference between the average firm (log) productivity in each country–industry–productivity group-year for each group in the bottom 40% of the productivity distribution and the average (log) productivity at the top 10% of the distribution in the same country–industry–year (i.e., $gap_{cjq,t-1} = \overline{P}^F_{cj,t-1} - \overline{P}_{cjq,t-1}$ with $q \in \{p(0-10), p(10-40)\}$).

In addition, X_j includes all main variables of interest, reflecting factors possibly directly affecting productivity growth and the strength of the catch-up effect. The main regressions include country-time and industry fixed effects, so that the direct effect of the factor of interest (ρX_j in Equation (7)) is absorbed by the fixed effects. Standard errors are clustered at the country–industry level, in order to account for the correlation of the residuals in an unconstrained way within country–industry.[25] Since the data in MultiProd are microaggregated moments (and means, in particular) from firm-level data, in all regressions we weight each observation (cjq, t) by the number of firms reporting nonmissing information for the relevant left-hand-side variable in a given country–industry–year–productivity group. The weighting strategy implies that our estimates are similar to those hypothetically generated using the underlying microdata samples.

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 measures the difference in the speed of catchup associated with one standard deviation of X and captures whether each considered factor X hinders or fosters laggards' catchup (X_j is standardized in all regressions). The variable $\overline{\Delta P}^{F}_{cjq,t}$ controls for the potential growth of the industry, and to some extent for country–industry–time-specific dynamics.

It is worth noting that the frontier for each industry is defined at the national level, instead of at the global level. Previous studies have shown that the productivity growth of laggard firms within a country is more strongly related to the productivity of the most advanced domestic firms, instead of to those (generally 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 and catch up with the national frontier. Given the focus on laggards, the national frontier seems therefore the right reference point to look at knowledge and technology diffusion and its determinants.[26]

The diffusion of technology and knowledge does not occur automatically, but requires a costly process of adoption, influenced by firms' capabilities and incentives to learn from the most innovative ones (e.g., Griffith et al., 2004). In addition, the digital transformation and the transition to a knowledge economy have increased the importance of complementary investments (Bloom et al., 2012; Andrews et al., 2016), thus raising further obstacles to a broad diffusion of technology and knowledge.

Therefore, our analysis investigates the heterogeneity of catchup across sectors, focusing in particular on the structural characteristics (X_j) related to digital and skill intensity presented in the previous section. A number of checks are performed to test the robustness of the main finding, that is, a lower catchup in digital- and skill-intensive industries. In particular, we reestimate Equation (14) excluding ICT producing industries, using productivity growth over five years instead of annual growth on the left hand-side, using a longer lagged productivity gap on the right-hand side, adding an additional interaction term between sectoral capital intensity and the productivity gap on the right-hand side, and estimating the equation over a restricted sample covering the period 2005 onward. These checks are discussed more in detail in Section 5.

4.1.2. *Diffusion and catchup of laggards.* In this section, we quantify the extent of the catch-up effect for laggard firms in a first baseline analysis that does not consider the necessity for absorptive capacity. Nevertheless, we explore whether the speed of catchup varies across different sectors of the economy and assess the influence of laggards' average age.

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

[26] Whereas the national frontier appears to be the most appropriate reference for this type of analysis, it might be worth exploring how laggards are connected to the global frontier. Unfortunately, due to the data collection process, which is carried out at the microlevel in each individual country and then aggregated, we cannot define a global frontier. In addition, previous studies have defined the frontier using absolute thresholds, such as selecting the top 4, 8, or 20 firms. Our data do not contain such information, preventing us from investigating the robustness of our results with these alternative frontier definitions. However, when establishing a national frontier at the country–industry level, a definition in relative terms ensures better cross-country comparability, particularly given the significant variation in the number of firms within each industry across different countries.

Table 4
PRODUCTIVITY GROWTH AND CATCHUP: BASELINE

(a) Labour Productivity

	(1)	(2)	(3)	(4)
LP gap	0.1932***	0.1956***	0.2180***	0.2813***
	(0.019)	(0.019)	(0.009)	(0.024)
LP gap × Serv. dummy			−0.0247	
			(0.017)	
LP gap × Av age (cell)				−0.0104***
				(0.002)
Adj. R^2	0.721	0.733	0.734	0.796
Observations	5946	5946	5946	3499
Num countries	13	13	13	7
LP growth top firms		✓	✓	✓
country–year sector FE	✓	✓	✓	✓

(b) Multifactor Productivity

	(1)	(2)	(3)	(4)
MFP gap	0.1346***	0.1346***	0.1709***	0.2151***
	(0.020)	(0.020)	(0.011)	(0.024)
MFP gap × Serv. dummy			−0.0409*	
			(0.021)	
MFP gap × Av age (cell)				−0.0078***
				(0.002)
Adj. R^2	0.447	0.447	0.452	0.596
Observations	5315	5315	5315	3193
Num countries	13	13	13	7
MFP growth top firms		✓	✓	✓
Country–year–sector FE	✓	✓	✓	✓

NOTE: This table reports the results from the estimation of Equation (14). Column (2) includes productivity growth of top firms as a control. Column (3) includes an interaction with a dummy variable that takes value 1 if the industry belongs to the nonfinancial market services sector. Column (4) includes an interaction with laggards' age, which represents the average age of firms in a given country–industry–productivity group-year. The *LP (MFP) gap* is computed as the difference between the average (log) productivity at the frontier (top 10% most productive firms in the same country, industry, and year) and firms in the two groups of laggards, p(0–10) and p(10–40). The control *LP (MFP) growth top firms* corresponds to the average LP (MFP) growth between $t-1$ and t of firms in the top decile of the LP (MFP) distribution at time $t-1$. Data are for manufacturing and nonfinancial market services. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, and SWE. Due to censoring on the firm birth year variable in some countries, regressions reported in column (8) include seven countries only: BEL, DNK, FRA, IRL, ITA, NOR, and SWE. Clustered standard errors at the country–sector level in parentheses: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 4 shows the baseline results. We first estimate coefficient β_1 of Equation (14) alone (column (1)), then we reestimate it controlling for the productivity growth of the frontier (column (2), estimate of λ not shown). Column (3) tests the potential difference between manufacturing and market services by further interacting the productivity gap with a dummy variable equal to 1 for nonfinancial market services and 0 for manufacturing. As a last exercise, we investigate the presence of differences in catch-up rates for firms at different stages of their life cycle, by interacting the productivity gap with the average age of laggards (column (4)).[27]

All regressions confirm a positive relationship between the productivity gap and the productivity growth of laggards, indicating the existence of convergence forces at the bottom of the distribution. Stated differently, a positive and significant coefficient for both LP (Table 4

[27] The age variable represents the average age of firms within a cell, that is, in a given country–industry–productivity group-year.

a) and MFP (Table 4 b), indicates that firms which are further behind the national industry-specific frontier experience, on average, higher rates of productivity growth.

We do not find strong evidence of differences across manufacturing and nonfinancial market services in column (3), where 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 belonging to nonfinancial market services. The difference is only marginally significant at the 10% level for MFP (Table 4 b) and is not statistically significant for LP (Table 4 a). This suggests that differences across sectors according to digital and knowledge intensity, presented in the rest of the article, do not only reflect differences between manufacturing and services. On the contrary, the results in column (4) show that younger laggard firms catch up more rapidly, which suggests that the composition of the group of laggards matters and confirms that younger firms have a higher potential for productivity growth.[28]

Finally, we examine the heterogeneity in the catch-up coefficient across industries (see Figure B.1 in the Online Appendix). The baseline model is therefore extended by interacting the productivity gap with a dummy for each industry. This exercise shows significant heterogeneity across industries in the speed of catchup. While the ranking differs for LP and MFP, some industries, such as legal and accounting, IT or computer and electronics, consistently appear at the bottom of catch-up rate.

4.1.3. *Slower catchup in digital- and knowledge-intensive industries.* We now investigate differences in the speed of catchup across industries with different levels of digital and knowledge intensity, which may reveal the existence of barriers to diffusion. More specifically, based on estimates of Equation (14), we test whether laggards catch up at a lower speed in sectors more exposed to digital technologies and knowledge, as well as requiring more skilled labor.

Tables 5(a) and (b) show the results of the main regressions for LP and MFP, respectively. Each column reports the link between the speed of productivity catchup and the industry characteristic X_j, specified as title of the column and described in detail in Subsection 3.4. Columns (1)–(6) explore the heterogeneity in catchup across industries with different degree of digitalization, whereas columns (7) and (8) focus on knowledge intensity. Given that in all regressions presented in Table 5, X_j varies at the industry level, the direct correlation of the variable with productivity growth of laggards is absorbed by the industry fixed effects.[29] This allows us to focus exclusively on the differences in the speed of convergence across industries, and thus to understand whether structural factors are associated with convergence or divergence forces.

All results in Tables 5(a) and (b) point in the same direction: laggards catch up at a lower speed in more digital- and knowledge-intensive industries. Whereas a higher use of digital technologies and knowledge may be beneficial for the overall productivity growth, they seem nonetheless to push toward divergence in productivity, possibly due to barriers preventing the rapid adoption of technology by laggards and hampering the diffusion of knowledge from frontier firms. On the contrary, laggards in less digital- and knowledge-intensive sectors are catching up faster with the frontier.

[28] Note that the age variable is available only for seven countries. Due to data availability constraints, we focus on the productivity growth of continuing firms, without being able to distinguish the growth of new firms from that of incumbents. Although the results in column (4) suggests that life-cycle dynamics of firms can play a role in the strength of catchup, we can rule out that the compositional effect due to selection on survival is the only driver of convergence. In the working paper version of this article (Berlingieri et al., 2020), we show via a Melitz and Polanec (2015) decomposition that entry and exit dynamics account for significant share of productivity growth only at the very bottom of the productivity distribution (in the p(0–10) group). Our baseline regressions are weighted by the number of firms in each cell, which is much higher in the p(10–40) group by construction. So, although life-cycle dynamics are an important component of convergence, they are not the only one.

[29] 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.

TABLE 5
PRODUCTIVITY GROWTH AND CATCHUP OF LAGGARDS: DIGITAL AND KNOWLEDGE INTENSITY

(a) Labor Productivity

	(1) Digital Dummy	(2) ICT Eq. Intensity	(3) Software Intensity	(4) ICT Goods Intermediate	(5) ICT serv. Intermediate	(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^2	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	✓	✓	✓	✓	✓	✓	✓	✓
Country–year–sector FE	✓	✓	✓	✓	✓	✓	✓	✓

(b) Multifactor Productivity

	(1) Digital Dummy	(2) ICT Eq. Intensity	(3) Software Intensity	(4) ICT Goods Intermediate	(5) ICT Serv. Intermediate	(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^2	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	✓	✓	✓	✓	✓	✓	✓	✓
Country–year–sector FE	✓	✓	✓	✓	✓	✓	✓	✓

NOTE: This table reports the results from the estimation of Equation (14), and each column corresponds to a different X_j reported as the title of the column. Specifically, in column (1) X_j corresponds to a dummy variable that takes value 1 if the industry is classified as digital-intensive in the global taxonomy developed by Calvino et al. (2018). In columns (2)–(5), X_j corresponds to individual indicators underlying the global taxonomy, namely: investment intensity in ICT equipment (2); investment intensity in software and database (3); ICT goods as intermediate inputs (4); ICT services as intermediate inputs (5). Then, X_j corresponds to the measure of ICT task intensity from Grundke et al. (2017) and Calvino et al. (2018) (column (6)); the share of hours worked by high-skill workers (column (7)); a dummy variable that takes value 1 if nonfinancial market services are classified as knowledge-intensive services (KIS) according to the Eurostat classification of KIS (column (8)). The *LP (MFP) gap* is computed as the difference between the average (log) productivity at the frontier (top 10% most productive firms in the same country, industry, and year) and firms in the two groups of laggards, p(0–10) and p(10–40). The control *LP (MFP) growth top firms* corresponds to the average LP (MFP) growth between $t-1$ and t of firms in the top decile of the LP (MFP) distribution at time $t-1$. All variables X are standardized, except in columns (1) and (8), where X denotes dummy variables. Data are for manufacturing and nonfinancial market services. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, and SWE. Clustered standard errors at the country–sector level in parentheses: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

The result holds for all facets of digitalization described in the previous section. In column (1), industries are divided into digital and nondigital based on the global digital taxonomy.[30] This shows that firms belonging to more digital-intensive sectors are catching up at a lower speed than those belonging to less digital ones.

The rate of catchup also appears lower in more digital-intensive industries when we focus on specific facets of the digital transformation. Columns (2) and (3) show that sectors characterized by more intensive investments in ICT, both tangible (column (2)) and intangible (column (3)), also display a lower speed of convergence through diffusion. This possibly reflects heterogeneity in the extent to which firms invest in ICTs within these sectors, since laggards may lack the capability and incentives to undertake such investments.

Another crucial aspect of digitalization 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. (2023) show that cloud computing services enable "a shift in the nature of ICT use, from investment in sunk capital to a pay-on-demand service," and enable firms (especially young ones) to rapidly scale-up in terms of both employment and productivity. Despite the new possibilities opened by this shift, columns (4) and (5) of Table 5 indicate a lower speed of catchup for laggards in industries where purchases of ICT goods and services as intermediate inputs are more prevalent. Therefore, the negative coefficients in column (5) seem in contradiction with the benefits associated with the higher accessibility of ICT services, such as cloud services. However, unreported additional results suggest that a higher use of ICT intermediates may not necessarily hamper the catchup of laggards and might, in fact, even increase the speed of catchup when other aspects of digitalization are accounted for. Together, these results may qualify the finding of DeStefano et al. (2023), by suggesting that ICT capital is a prerequisite to benefit from ICT services, such as cloud computing. More generally, a broader use of ICT services also requires complementary investments in enabling infrastructures, ICT capital, and 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 (Online Appendix, Figure B.2), which shows that the use of such services remains heterogeneous across firms. Several types of barriers could explain such heterogeneity. First, as mentioned above, while ICT services largely facilitate the access to digital technologies, they do not completely eliminate the need for absorptive capacity and complementary investments. For instance, using cloud services requires ICT skills and a stable and high-speed broadband connection (which may be more expensive or even not available in some geographical areas).[31] Second, 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, the digital transformation also affects the content of jobs and the change in the mix of skills required by firms. Looking at digitalization from the human capital side, column (6) of Table 5 shows that laggards catch up at a lower speed if they belong to those industries in which ICT tasks are more prevalent. 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 where such skills are in high demand. Due to the cost of training workers, laggard 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., 2018), laggards may face greater difficulties in attracting talented workers with the right skills.

[30] 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 Subsection 3.4 for a more detailed description.

[31] Geographical disparities in the access to enabling infrastructures may be an important barrier to catchup if laggards are more represented in less favored areas.

Similarly, laggards further behind the frontier catch up at a lower speed in industries characterized by a higher share of hours worked by high-skilled workers (column (7)). The result also holds when nonfinancial market services are divided into a group of KIS and less knowledge-intensive ones (column (8)). The mechanisms are likely to be very similar to those discussed above. The slower catchup in knowledge-intensive industries may reflect the fact that educated workers are highly sought by firms, putting an 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., 2021).

Overall, the lower speed of catchup in digital- and skill-intensive sectors suggests stronger barriers to diffusion of technology and knowledge in these sectors. The diffusion of technology and knowledge is not mechanical, but requires a costly process of adoption which depends on firms' capabilities and incentives. The digital transformation and the transition to a knowledge economy seem to have intensified the role of capabilities and incentives, raising further barriers to a broad diffusion of technology and knowledge. Brynjolfsson et al. (2017) stress that it takes considerable time to sufficiently harness new technologies. This is especially true for those major new technologies that ultimately have an important effect on aggregate productivity and welfare: general-purpose technologies.

One possible barrier to diffusion related to the digital and knowledge economy is that investments in intangible assets have become more necessary to catchup with leaders and to outperform competitors. For example, the transition to an economy based on ideas makes human capital a particularly relevant dimension of intangible assets, reinforcing the need for good management and training of workers. Similarly, the digitalization 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 labor, 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 direct and complementary investments, potentially hampering the diffusion process.[32]

The existence of potential barriers to adoption (cost, capabilities, and incentives) implies that the penetration of new technologies may be not only slow but also potentially heterogeneous across groups of firms. As an illustration, Figures B.2 and B.3 in the Online 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 B.2) and in the access to high-speed broadband (Figure B.3) between large (more than 250 employees) and small firms (10–49 employees) for the first and last available years in each country. First, for all countries these figures highlight significant differences in the level of adoption in the two groups of firms. Second, and more importantly, these figures also show a noticeable increase in the differential rate of adoption between large and small businesses over time.[33] Overall, this shows a more rapid penetration of technologies in large firms than in small ones (Lashkari et al., 2024). Firms at the frontier (on average larger) may maintain a technological gap through

[32] Chiavari and Goraya (2023) document that investment in intangible capital is subject to higher adjustment costs than tangible capital.

[33] Causality cannot be inferred: on the one hand large firms may be able to adopt more easily new technologies; on the other hand, early adoption may allow firm to scale up more rapidly.

rapid adoption of technology, whereas laggards may face increasing barriers to adoption. Consequently, industries which are more exposed to the digital transformation may also be more likely to be characterized by a higher heterogeneity in the adoption of new technologies across firms, with possible negative consequences on the speed of catchup.

4.2. *Productivity Dispersion and Digital and Skill Intensity.* We showed the existence of a catch-up effect that increases productivity growth at the bottom and contributes to productivity convergence. However, an extended literature has also documented large productivity gaps, driven by divergence forces related to differences in technology and the stock of knowledge (in particular, ICT and R&D), the quality of inputs, the organization of production, managerial quality, and product innovation (see Syverson, 2011). Existing productivity gaps, therefore, result from the equilibrium of convergence mechanisms (diffusion) and differences across firms, particularly regarding their ability to innovate. As sketched in the theoretical framework, the catch-up equation implies that the long-run equilibrium level of productivity dispersion is negatively correlated to the speed of catchup. Stated differently, a lower speed of catchup results in a higher level of productivity dispersion, reflecting the slower diffusion of innovation. Hence, the contemporaneous existence of catchup and divergence in productivity is explained by an equilibrium outcome reflecting a tension between differences in firms' innovative capabilities, which tend to increase dispersion, and productivity catchup, which tends to reduce dispersion.

The next step of the article is therefore to evaluate the link between levels of productivity dispersion and the sectoral characteristics in terms of digital and skill intensity used in the previous analysis. More formally, the prediction of a positive correlation is tested with a regression of a standard measure of dispersion, the "90–10 ratio," on relevant indicators of digital and knowledge intensity at the industry level, including country–year fixed effects. We estimate the following equation:

$$gap_{cj,t}^{90-10} = \alpha + \gamma X_j + \delta_{ct} + u_{cj,t}, \tag{15}$$

where $gap_{cj,t}^{90-10}$, the measure of productivity dispersion, is the difference between the 90th and the 10th percentile of the (log) productivity distribution (i.e., $gap_{cj,t}^{90-10} = P_{cj,t-1}^{90} - P_{cj,t-1}^{10}$); X_j are sectoral measures of digital and knowledge intensity, and refer to the characteristics detailed previously; δ_{ct} denotes country–year fixed effects, which allow to control for country–years macro trends.[34] 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 catchup and the long-term equilibrium level of productivity dispersion.

Estimates reported in Tables 6(a) and (b) for LP and MFP, respectively, all confirm a positive and significant correlation between productivity dispersion and the measures of digital and knowledge intensity. This finding confirms that barriers to diffusion, by inducing a lower catchup in digital- and skill-intensive sectors, contribute to higher firm heterogeneity. This also 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, and the results from Corrado et al. (2021) showing that productivity dispersion has increased more in intangible-intensive industries.

4.3. *Catchup and Barriers to Diffusion: The Role of the Economic Environment.* Our analysis shows that higher digital intensity and skill requirements are associated with a lower speed of productivity catchup of laggards, and that this translates into higher productivity dispersion. These results suggest that barriers to technology and knowledge diffusion play an important role. Digital technologies and intangibles have changed the way firms produce and

[34] Note that industry fixed effects would absorb the main coefficient of interest.

TABLE 6
PRODUCTIVITY DISPERSION AND DIGITAL AND KNOWLEDGE INTENSITY

(a) Labor 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
X	0.2887***	0.2586***	0.1484***	0.1694***	0.0870***	0.1337***	0.1723***	0.2746***
	(0.068)	(0.037)	(0.034)	(0.050)	(0.027)	(0.035)	(0.036)	(0.088)
Adj. R^2	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	✓	✓	✓	✓	✓	✓	✓	✓

(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
X	0.1452***	0.2013***	0.0991***	0.0916**	0.0586**	0.0820***	0.1007***	0.1606**
	(0.047)	(0.032)	(0.028)	(0.044)	(0.027)	(0.030)	(0.029)	(0.068)
Adj. R^2	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	✓	✓	✓	✓	✓	✓	✓	✓

NOTE: This table reports the results from a regression, based on Equation (15), of productivity dispersion on industry characteristics X_j, reported as title of the column. Specifically, in column (1), X_j corresponds to a dummy variable that takes value 1 if the industry is classified as digital-intensive in the global taxonomy developed by Calvino et al. (2018). In columns (2)–(5), X_j corresponds to individual indicators underlying the global taxonomy, namely: investment intensity in ICT equipment (2); investment intensity in software and database (3); ICT goods as intermediate inputs (4); ICT services as intermediate inputs (5). Then, X_j corresponds to the measure of ICT task intensity from Grundke et al. (2017) and Calvino et al. (2018) (column (6)); the share of hours worked by high-skill workers (column (7)); a dummy variable that takes value 1 if nonfinancial market services are classified as knowledge-intensive services (KIS) according to the Eurostat classification of KIS (column (8)). Productivity dispersion is computed as the difference between the 90th and 10th percentile of the log productivity distribution, for both LP and MFP. Data are for manufacturing and nonfinancial market services. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, and SWE. Clustered standard errors at the country–sector level in parentheses: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

compete, and firms are heterogeneous regarding their capacity and incentives to adapt to such changes (e.g., Haskel and Westlake, 2017).

Significant barriers may be particularly related to accessing workers with the right skills, accessing funding to finance costly investments in technology and complementary assets, and performing innovative activities to build absorptive capacity. The economic environment in which firms operate may in turn shape such barriers. To provide additional support to our results, we show that catch-up rates tend to be lower in countries where such barriers are likely to be more prevalent, especially for firms operating in digital- and skill-intensive industries.

For this purpose, we enrich Equation (14) as follows:

$$
\begin{aligned}
\Delta P_{cjq,t} &= \alpha + \beta_1 gap_{cjq,t-1} + \beta_2 (gap_{cjq,t-1} \times X_j) + \beta_3 (gap_{cjq,t-1} \times Pol_{c,t-1}) \\
&+ \beta_4 gap_{cjq,t-1} \times (Pol_{c,t-1} \times X_j) + \beta_5 (Pol_{c,t-1} \times X_j) \\
&+ \gamma (gap_{cjq,t-1} \times GDPpc_{c,t-1}) + \lambda \Delta P^F_{cjq,t} + \delta_{ct} + \tau_j + \varepsilon_{cjq,t},
\end{aligned}
\tag{16}
$$

where, as previously, X_j denotes industry-level digital and knowledge intensity indicators, capturing the extent to which these industries are exposed to the transition to a digital and knowledge economy. $Pol_{c,t-1}$ denotes country level (time-varying) variables proxying for economic environments and policies that have the potential to influence the speed of catchup.[35] $gap_{cjq,t-1}$ still denotes the (labor or multifactor) productivity gap between laggards and the national frontier, whereas δ_{ct} and τ_j are country–year and industry fixed effects as before. For ease of interpretation, both $Pol_{c,t-1}$ and X_j (when not a dummy variable) are standardized. Equation (16) also includes the gap interacted with GDP per-capita in a given country–year, in order to control for the fact that barriers to diffusion might be correlated with the level of development of a country. Standard errors are clustered at the country–industry level.

For this analysis, the main coefficients of interest are the estimates of β_2, β_3 and, especially, β_4. 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 catchup at the average level of Pol. β_3 measures the relation between Pol and the speed of catchup when $X_j = 0$, that is, for the average level of the digital and knowledge intensity indicators (or for nondigital industries when X_j is the digital dummy). β_4 accounts for the additional "effect" (not in a causal sense) of Pol on catchup for high levels (one standard deviation above the mean) of the digital and knowledge intensity indicators, or for digital industries when X_j is the digital dummy. Importantly, when $\beta_4 \neq 0$, the relation between industry characteristics and the speed of catchup depends on the economic environment prevailing in the country. For brevity, estimates of Equation (16) are presented for two industry characteristics (X_j) only: (i) the dummy variable for digital industries, and (ii) the measure of skill intensity.[36]

Estimating Equation (16), we focus on three possible indicators of barriers to diffusion described in detail in Subsection 3.5. We first focus on an indicator of the allocation of human resources using the share of workers whose educational attainment level is well matched to the level required in their job. We then investigate whether catchup is lower in country–industries in which access to finance may be more difficult or costly for laggards, using the interest spread between large and small firms as a proxy for the differential cost of external finance between frontier and laggard firms. Finally, we investigate whether differences in government financed business expenditures on R&D, which are likely to boost the absorptive capacity of laggards, are associated with differences in catch-up rates, especially in digital- and skill-intensive industries.

Overall, results displayed in Table 7 are consistent with lower catch-up rates in digital- and skill-intensive industries, reflecting a slower diffusion of technology and knowledge. Columns (1) and (2) suggest that catchup is faster in countries with a better matching of workers and jobs in terms of skills. The positive association between skill-matching and speed of catchup tends also to be stronger in digital- and skill-intensive industries, where skills are key to adopting new technologies and using them efficiently. The role of human capital for the diffusion of technologies has been emphasized for a long time. In Benhabib and Spiegel (1994), human capital levels affect not only the capacity to innovate but also the speed of technological catchup and diffusion. Griffith et al. (2004) find similar results. In addition, the digital transformation and rising importance of complementary intangible assets may also affect the bundle of skills that are required for the diffusion process and the relative demand for different occupations. Our results confirm that lack of human capital and skill mismatch may be significant barriers to catchup in digital- and skill-intensive industries. Such barriers may be particularly relevant for laggard firms, which may have difficulties attracting workers with relevant skills due to lower wages associated with their lower productivity.[37]

Columns (3) and (4) show that catchup is lower in digital- and skill-intensive industries, especially in countries where the cost of external finance for small firms is higher relative to the cost for large firms (as reflected in higher interest rate spreads). Laggard firms might face

[35] In the following, the term policy is used to refer to elements of the economic environment that could also be related to policies directly or indirectly.

[36] Results are robust to the use of the alternative measures of digitalization and skill intensity considered in the article.

[37] See Berlingieri et al. (2018) on the relationship between productivity and wages using MultiProd data.

Table 7
BARRIERS TO CATCHUP

(a) Labor Productivity	Sh. Well Matched		Spread Large–Small		BERD Financed by Gov (%BERD)	
	(1) Digital Dummy	(2) H-SKill Sh.	(3) Digital Dummy	(4) H-SKill Sh.	(5) Digital Dummy	(6) H-SKill Sh.
LP gap	0.2369***	0.2257***	0.1872***	0.1724***	0.2023***	0.1837***
	(0.012)	(0.009)	(0.018)	(0.014)	(0.013)	(0.011)
LP gap × Ind	−0.0333**	−0.0178***	−0.0442**	−0.0248***	−0.0576***	−0.0318***
	(0.015)	(0.006)	(0.021)	(0.009)	(0.017)	(0.007)
LP gap × Pol	0.0382***	0.0475***	0.0073	0.0034	−0.0052	0.0021
	(0.009)	(0.007)	(0.008)	(0.006)	(0.007)	(0.006)
LP gap × Pol × Ind	0.0187*	0.0099**	−0.0208**	−0.0077**	0.0282***	0.0118***
	(0.011)	(0.005)	(0.009)	(0.004)	(0.009)	(0.004)
Pol × Ind	−0.0271	−0.0212**	0.0422**	0.0110	−0.0611***	−0.0221***
	(0.023)	(0.010)	(0.019)	(0.008)	(0.018)	(0.008)
Adj. R^2	0.853	0.854	0.765	0.773	0.801	0.807
Observations	4886	4886	2428	2428	4565	4565
Num countries	11	11	12	12	12	12
LP growth top firms	yes	yes	yes	yes	yes	yes
Country–year–sector FE	yes	yes	yes	yes	yes	yes

(*Continued*)

Table 7
(continued)

(b) Multifactor Productivity	Sh. Well Matched		Spread Large–Small		BERD Financed by Gov (%BERD)	
	(1) Digital Dummy	(2) H-SKill Sh.	(3) Digital Dummy	(4) H-SKill Sh.	(5) Digital Dummy	(6) H-SKill Sh.
MFP gap	0.1723***	0.1714***	0.1450***	0.1356***	0.1651***	0.1535***
	(0.015)	(0.015)	(0.015)	(0.011)	(0.015)	(0.011)
MFP gap × Ind	−0.0087	−0.0021	−0.0377*	−0.0160	−0.0577***	−0.0268***
	(0.022)	(0.010)	(0.021)	(0.010)	(0.016)	(0.007)
MFP gap × Pol	0.0134*	0.0235***	0.0100	0.0080	−0.0062	−0.0009
	(0.008)	(0.007)	(0.009)	(0.006)	(0.010)	(0.008)
MFP gap × Pol × Ind	0.0218**	0.0069	−0.0277***	−0.0146***	0.0288**	0.0200***
	(0.010)	(0.005)	(0.009)	(0.004)	(0.013)	(0.006)
Pol × Ind	−0.0807***	−0.0340***	0.0550**	0.0213*	−0.0463*	−0.0310**
	(0.024)	(0.013)	(0.025)	(0.011)	(0.027)	(0.012)
Adj. R^2	0.598	0.604	0.511	0.529	0.519	0.541
Observations	4249	4249	2365	2365	4102	4102
Num countries	11	11	11	11	12	12
MFP growth top firms	yes	yes	yes	yes	yes	yes
Country–year–sector FE	yes	yes	yes	yes	yes	yes

Note: This table reports estimates based on Equation (16). *LP (MFP) gap* is computed as the difference between the average (log) productivity at the frontier (top 10% most productive firms in the same country, industry, and year) and firms in the two groups of laggards, p(0–10) and p(10–40). The control *LP (MFP) growth top firms* corresponds to the average LP (MFP) growth between $t-1$ and t of firms in the top decile of the LP (MFP) distribution at time $t-1$. All variables X_j are standardized, except in columns (1), (3), and (6) where X denotes dummy variables. Data are for manufacturing and nonfinancial market services. All regressions also include the interaction between the productivity gap and GDP per capita at $t-1$. Countries included: AUS, BEL, CAN, CHE, DNK, FIN, FRA, HUN, IRL, ITA, NOR, PRT, and SWE. Clustered standard errors at the country–sector level in parentheses: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

bigger difficulties financing investments in both tangible and intangible assets, for instance, because their lower size and age may be associated with higher financial constraints (e.g., Gertler and Gilchrist, 1994; Whited and Wu, 2006; Hadlock and Pierce, 2010). Financing frictions for laggards can, in turn, undermine their ability to catch up due to reduced investments in digital technologies and complementary intangibles assets, which are more difficult to finance (Almeida and Campello, 2007; Caggese and Pérez-Orive, 2022). The characteristics of intangible capital might further impede its financing, particularly due to asymmetries of information (e.g., difficulty to assess the quality of a project) and low pledgeability, and might therefore reduce the incentives and ability of laggards to invest in new technologies and acquire knowledge.

Columns (5) and (6) show that a higher share of business expenditures directly financed by governments is associated with higher catch-up rates in digital- and skill-intensive industries. This is consistent with the "second face of R&D" (e.g., Griffith et al., 2004). Not only R&D fosters innovation, but it also enhances technology transfers by increasing firms' absorptive capacity. By engaging on R&D, firms accumulate a tacit knowledge that allows them to understand and assimilate existing technology and innovations. However, the concentration of business expenditures on R&D suggests that low-productivity firms—generally younger and smaller—may also lag in terms of their efforts devoted to R&D. Evidence displayed in Table 7 supports the interpretation that the slower catchup in digital- and skill-intensive industries may be related to a lack of absorptive capacity of laggards that may struggle to adapt to faster changes in technology and knowledge in these industries. However, direct funding of business expenditures on R&D by the government has the potential to significantly affect R&D efforts of small and young firms. Direct public funding of business expenditures on R&D indeed takes various forms, such as competitive grants, debt financing (loans), risk-sharing mechanisms, or public procurement (OECD, 2016). These instruments may be particularly relevant for laggards. For instance, grants, loans, and risk sharing through credit guarantees schemes can reduce the cost of R&D and improve access to finance for otherwise financially constrained firms. On the other hand, 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 commercialization phase.

4.4. *Declining Catch-Up Rates over Time.* We conclude this section by extending the baseline catch-up equation to assess possible changes in the speed of catchup over time. Andrews et al. (2016) have documented a decline in the speed of convergence, and this decline suggests that the diffusion of technology and knowledge has slowed down over time. Interestingly, Andrews et al. (2016) find a stronger decline in diffusion when focusing on a measure of MFP corrected for markups, suggesting that the observed decline is not driven by changes in the market structure, but rather by a technological divergence. The decline in the intensity of knowledge diffusion is also discussed by Akcigit and Ates (2021, 2023) who show that the slowdown in knowledge diffusion may in fact be the main driving force of a number of recent empirical trends, such as increasing productivity dispersion, rising market concentration, and a slowdown in business dynamism.

Using the data at hand, we assess the potential slowdown in diffusion by modifying the baseline specification equation (14) to interact the productivity gap with year dummies. As this specification with year dummies is more demanding, we include country, industry, and year fixed effects separately. Results, reported in Figure B.5 in the Online Appendix, provide further evidence that the speed of catchup has declined over time, suggesting increasing barriers to the diffusion of technology and knowledge.

5. ROBUSTNESS AND ADDITIONAL RESULTS

In this section, we provide some robustness checks to corroborate our results and the interpretation that the association between industry characteristics and the lower speed of catchup reflects barriers to diffusion related to the importance of skills and digital technologies.

First, we show that our results are not driven by ICT-producing industries and their growing importance. In this article, we show that diffusion is slower in industries that are more ICT-intensive and we claim that it is due to barriers hampering a broad adoption of these technologies. A first concern is related to the possibility that our results are driven by the increasing importance of ICT-producing sectors instead of reflecting barriers associated with the broad usage of ICT in all other industries of the economy.[38] The following SNA A38 two-digit industries are classified as ICT-producing: 26 "Computer, electronic, and optical products," 58–60 "Publishing, audiovisual, and broadcasting activities," 61 "Telecommunications," and 62–63 "IT and other information services." We therefore estimate regressions on a sample excluding these industries. Estimates are presented in Tables C.5(a) and (b) in the Online Appendix. They 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 toward ICT industries and instead suggest that barriers to diffusion are related to the importance of ICT in all sectors.

A common issue in the estimation of the catch-up equation is related to measurement error. Average firm (log) productivity $\overline{P}_{cjq,t-1}$ appears both on the left- and right-hand sides of the specification. Measurement error in $\overline{P}_{cjq,t-1}$ could therefore lead to a spurious correlation between productivity growth and the productivity gap. To reduce this concern, we replace the gap by its three-period lag, $gap_{cjq,t-3}$.[39] Results are qualitatively and quantitatively very similar (Online Appendix Table C.6).

An additional concern arises from the possibility that the correlation between productivity growth and the distance from the frontier reflects mean reversion dynamics instead of a productivity catchup related to diffusion. Such mean reversion can arise from temporary negative productivity shocks that induce both larger productivity gap and faster subsequent growth, as productivity is reverting to the equilibrium value.[40] To mitigate this concern, we check our results with 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 $t+2$, $t+3$, $t+4$, and $t+5$.[41] This variable, therefore, considers productivity growth over a five-year horizon, which should attenuate the effect of mean reversion induced by transitory shocks. Note also that this average of annualized growth rates is less subject to measurement error in any particular horizon $t+j$ compared to any growth rate based on two years only. Results from this regressions are displayed in Online Appendix Tables C.7(a) and (b) and confirm both the existence of the catch-up effect for laggards and the lower diffusion in digital- and skill-intensive industries.

To further show that our results are not driven simply by mean reversion, we estimate a variation of the model in which the productivity at the frontier and the productivity of laggards enter separately in the model, instead of the productivity gap. If the higher productivity growth of laggards was driven only by reversion to the mean, the growth between time t and $t+1$ would be driven by the level of productivity for laggards at time t, independently of

[38] Because we use weighted regressions, an increase in the weight of ICT industries would be an additional concern. Figure B.4 in the Online Appendix plots, for each country, the share of firms in ICT-producing industries in manufacturing and nonfinancial market services over time, and shows that the increase is relatively modest in our data.

[39] Note that $gap_{cjq,t-3}$ measures the productivity gap of firms in the productivity group q (in country c industry j) in $t-3$, which is not necessarily populated by the same firms as the group q in $t-1$. The two measures, however, are significantly correlated.

[40] Suppose, for instance, that employment is predetermined and there is a one-time negative shock to firms' demand, resulting in lower VA. This would result in a negative LP shock, but, in the next period, the effect of the demand shock disappears and productivity reverts to its equilibrium value, which is reflected into a higher productivity growth. Similarly, persistent shocks to VA coupled with employment adjustment costs could induce such mean reversion dynamics.

[41] The growth rate is therefore $\overline{\Delta P}_{cjq,t\to t+5} = (\overline{\Delta P}_{cjq,t\to t+2} + \overline{\Delta P}_{cjq,t\to t+3} + \overline{\Delta P}_{cjq,t\to t+4} + \overline{\Delta P}_{cjq,t\to t+5})/4$, where $\overline{\Delta P}_{cjq,t\to t+j}$ is the average across firms in a country–sector–productivity group-year of annualized log-productivity growth, between t and $t+j$. This also corresponds to a weighted average of the growth from t to $t+1$, $t+1$ to $t+2$, $t+2$ to $t+3$, and $t+4$ to $t+5$, with weights decreasing with the horizon considered.

the position of the frontier. Results in Table C.8 in the Online Appendix show that both the level of productivity of laggards and the level of productivity of the frontier are related to the growth of laggard firms. Furthermore, the interaction terms of the productivity at the frontier with measures of digital intensity and KIS industries is negative and generally statistically significant. This suggests that the position of the frontier matters, supporting the interpretation of the results as a productivity catchup.

Another concern could be that the lower speed of catchup in digital- and knowledge-intensive sectors might reflect other characteristics beyond digital and/or knowledge intensity, which are however correlated with them. In particular, our result could be due to differences in technologies that are not related to digital or skill intensity. For instance, laggards may catch up at a lower speed in sectors with higher technological intensities, as reflected by their capital–labor ratio. This could arise, for instance, from higher constraints for laggards to invest in overall physical capital (e.g., due to financial constraints). To address this potential issue, results presented in Online Appendix Table C.9 also include an interaction term between the productivity gap and an industry-level measure of capital intensity, the capital–labor ratio.[42] These results show that there is no significant difference in the speed of catchup among firms belonging to industries with different levels of capital intensity. On the contrary, the estimated coefficients of digital and knowledge intensity are robust to the interaction of the productivity gap with a measure of capital intensity.

Digital and knowledge-intensive industries may be prone to generate concentration dynamics which may impede the growth of laggard firms and their catchup. To account for such dynamics, we extend the model to account for a measure of industry concentration that enters directly and as an interaction term with the productivity gap. Concentration is measured as a normalized Herfindahl–Hirschmann index (HHI) for sales. Results presented in Table C.10 in the Online Appendix show that the lower catch-up rate in digital and knowledge-intensive industries holds after controlling for concentration, and provide suggestive evidence that higher concentration may be related to lower catch-up rates of laggards. These results are further confirmed with an alternative measure of concentration based on the output share of firms in the top 10% of the sales distribution (results are available upon request).

Finally, we estimate our results on a restricted sample, which excludes the earliest years, focusing on a period for which most sectoral measures of digital and skill intensity are predetermined. In our main regressions, the sample covers the period 1995–2014, depending on data availability (see Table 1), but our measures of digital and skill intensity are computed over the periods 1995–2000, 2000–3, or later years (depending on the variable considered), potentially raising concerns about the endogeneity of our measures of digital and skill intensity. Table C.11 in the Online Appendix presents estimates based on a sample starting in 2005, which leads to very similar results.[43]

6. CONCLUSIONS

Thanks to a data set containing harmonized microaggregated statistics representative of the whole population of firms in 13 countries, this article provides new evidence on the diffusion of technology and knowledge to laggard firms and on the characteristics of these firms. We find that laggards, defined as firms belonging to the bottom 40% of the productivity distribution, are on average smaller and younger than the median firm. In addition, they display higher productivity growth than firms in the rest of the distribution. These findings suggest that the left tail of the productivity distribution is partly populated by small and young firms with a potential for growth.

[42] The capital–labor ratio is computed as the cross-country median value computed over the period 1995–2000 based on the OECD STAN data.

[43] Results are also robust when further restricting the sample.

We further explore the productivity catchup of laggard firms by looking at the relationship between their productivity growth and their distance to the frontier (the productivity gap) in a neo-Schumpetarian framework. Our empirical framework accounts for heterogeneity in catchup, as in Griffith et al. (2004), and focuses on diffusion from the national frontier, as in Bartelsman et al. (2008). Our results confirm a positive relationship between the productivity gap and the productivity growth of laggards, indicating that laggards benefit from convergence forces. In this respect, our article shows that the national frontier exerts a pull on the productivity of laggards, corroborating the findings of Bartelsman et al. (2008) for a large sample of countries, and supporting models of technology and knowledge diffusion.

We then explore the heterogeneity in the speed of catchup across industries according to structural characteristics related to digital and knowledge intensity, and we provide robust evidence that laggards are catching up at a lower speed in industries that are more digital- and knowledge-intensive. We further present corollary evidence that these industries display higher levels of dispersion. Overall, results suggest that a high level of technological intensity implies that laggard firms need to sustain high levels of investment to reach the technological level of their sector, or they need advanced skills to succeed in a knowledge-intensive sector. In digital- or knowledge-intensive industries, laggard firms may require higher absorptive capacity, making it more challenging for them to catch up with the frontier.

The lower catchup in digital- and knowledge-intensive industries might reflect barriers to diffusion, preventing advances in technology and knowledge to fully benefit all firms, especially in dynamic sectors. The article focuses on three types of possible barriers that may prevent the diffusion in digital- and knowledge-intensive industries: (i) access to human capital in a context of possible skill shortages, (ii) financing conditions, and (iii) the importance of firms' absorptive capacity in the form of R&D. Exploiting differences in the economic environment across countries, we find a more negative relationship between digital/knowledge intensity and the speed of catchup in countries where these obstacles are likely to be more prevalent. First, the negative correlation between digital/skill intensity and the speed of catchup is stronger in countries with higher mismatch between workers' education level and the level required for their jobs. Second, higher costs of external finance for SMEs (proxying for laggards) are also linked with a negative relationship between digital/knowledge intensity and catchup, suggesting that financing may also be a relevant barrier to diffusion in these industries. Third, higher support to laggards' absorptive capacity, proxied by more generous (direct) public funding of business expenditures on R&D, is associated with a higher speed of catchup in digital- and skill-intensive industries.

Overall, our findings support the hypothesis that the increasing productivity dispersion among firms might be a sign of stalling technological diffusion, due to difficulties for firms lagging behind to adapt to an economy increasingly based on knowledge and digital technologies. The article further provides additional evidence of a decline in the speed of catchup over time, which supports the hypothesis that knowledge diffusion has slowed down (in line with Andrews et al., 2016 and Akcigit and Ates, 2023). The article therefore contributes to the debate on the increasing productivity divergence among frontier and laggard firms (e.g., Andrews et al., 2016; Decker et al., 2020; Berlingieri et al., 2024) and on the productivity growth slowdown (e.g., Fernald, 2015; Decker et al., 2017; Syverson, 2017). In light of this debate, our results are important and can have far-reaching implications. As highlighted by Akcigit and Ates (2023), slower diffusion may reduce innovation at the frontier and contribute to several widely debated macro trends: increasing productivity dispersion, rising market concentration and markups, declining labor shares, and declining business dynamism.

DATA AVAILABILITY STATEMENT The data that support the findings of this study are available from the institutions listed in Desnoyers-James et al. (2019). Restrictions apply to the availability of these data, which were accessed via approved researchers for this study. All the programs used for this study as well as microaggregated data for France are available at http://bit.ly/IERE12748 with the permission of CASD - Centre d'accès sécurisé aux données.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Online Appendix

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