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Mark-ups in the digital era

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Abstract
Relying on a novel dataset which combines balance sheet data on firms, patents, and industry-level proxies of technology for 25 countries in the period 2001-2014, we document an increase in mark-ups over time, mainly driven by firms in the top half of the mark-up distribution, and a significant and increasing "mark-up gap" between firms in digital intensive and less digital intensive industries. Second, we show that the intangible components of the digital transformation, matter above all others for firm mark-up, and that this is not explained by the industry's fixed-cost structure, concentration, openness to trade and product market regulation.

Keywords: mark-ups, market power, digitalisation, intangible assets
JEL Codes: D2; L1; L2; O33

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1. Introduction

Over the last few years there has been an active debate among economists and policy makers about a number of well-documented macro-trends: increase in mark-ups and their dispersion (De Loecker et al., 2020; Hall, 2018); increase in concentration (Autor et al., 2020; Bessen, 2020; Gutiérrez and Philippon 2017a,b, 2018; Bajgar et al., 2019); declining business dynamism (Akcigit and Ates, 2019b and 2021; Decker et al., 2017; Bessen et al., 2020); decline in labour shares (Autor et al., 2017 and 2019; Barkai, 2020); increase in profit dispersion (Barkai, 2020; Bessen, 2020); and productivity slowdown and divergence (Andrews et al., 2016; Berlingieri et al., 2017). All these trends point to a polarisation of the business environment over time, leading to increased dispersion in firms' outcomes.

Despite the growing body of literature detailing these trends, the evidence is mostly U.S.-centred, and often on listed companies only. Very little is known about these patterns for privately owned firms across industries and countries. More importantly, consensus has yet to be reached on the underlying causes. The present paper contributes to this literature by exploring trends in firm mark-ups for private firms over a large set of countries, and testing the role of technology heterogeneity for the increased polarisation of industries against possible alternative explanations such as international competition and product market regulation. We focus in particular on digital technologies and their different components and find a prominent role for ICT-related intangible assets in shaping mark-up dynamics.

We therefore first document the main trends in the evolution of mark-ups, as well as their dispersion, for a broad set of countries, since 2000. An increase in mark-ups over time has been recently documented by few papers, often focusing exclusively on the U.S. and on listed firms (e.g., De Loecker at al., 2019; Hall, 2018), or in a broader set of countries than the U.S but only on publicly traded companies., namely Diez et al. (2018) and De Loecker and Eeckhout (2018a).[2] Our study is the first to investigate changes in mark-ups across listed and non-listed firms in 25 countries, for both the manufacturing and non-financial private business services sectors, over the period 2001-2014 (using the Orbis dataset). We estimate firm mark-ups applying the De Loecker and Warzynski (2012) methodology, who build on Hall (1988), and

[2] The paper by Diez et al., (2018) and De Loecker and Eeckhout (2018a) differ from ours also in the use of very different inputs in the production function (namely cost of goods sold, rather than labour and intermediates), as will be highlighted below.

we show that firm mark-ups have increased over time in a cross-country setting. Moreover, we provide evidence that this increase has been mainly driven by increases in the top half of the mark-up distribution, underlying an increase in mark-ups dispersion.

Next, we assess for the first time how firm mark-ups relate to diffusion and adoption of digital technologies. On the one hand, digital technologies allow instantaneous access to multiple geographical and product markets, cheaper business experimentation, easier sharing of ideas, and global reach in terms of inputs and customers. These forces, by levelling the playing field and allowing for easier market entry and market tipping, are bound to decrease firm mark-ups. On the other hand, digital technologies, like other general-purpose technologies, take time to diffuse (Jovanovic and Rousseau, 2005; Brynjolfsson et al., 2020 and 2021) and require a set of complementary investments in intangible assets that are costly and slow to implement. These knowledge assets can be used with close-to-zero marginal cost, allowing for faster scale-up in innovative companies. In addition, digital industries are typically characterised by: i) network effects, both direct and indirect, ii) economies of scope in data collection and analysis, and, thanks to this information, iii) high and increasing levels of price and product differentiation thanks to data analytics. Lastly, much of the innovativeness and know-how of digital technologies may be protected by intellectual property rights providing legal protection that limits diffusion. Over time, these characteristics may help industry leaders sustain and advance their position in the market and slow down the growth of competitors.

We therefore first correlate mark-up with a synthetic indicator of the digital intensity of industries, as developed by Calvino et al. (2018) based on several proxies of digital technologies. We find that firms operating in digital intensive industries enjoy on average higher mark-ups, and that differences in mark-ups between firms operating in digital and less digital industries have become significantly larger over time. Moreover, we find that these correlations differ between manufacturing and service industries, and in particular that: i) overall, firms operating in the services sector display higher mark-ups than firms operating in manufacturing; ii) the correlation between digital intensity and mark-ups is stronger in services than in manufacturing; and iii) within the services sector, the correlation is much stronger for firms operating in digital intensive industries.

Having established a positive correlation between mark-ups and an overall measure of the digital transformation of the economy, we investigate which features of digital technologies matter the most for mark-up dynamics. We consider how mark-ups are related to each facet of the digital intensity indicator and to the firm's ability to produce ICT-related innovations, as proxied by patents. To limit the scope of omitted variable bias in the estimated relationship between mark-ups and technology, this analysis leverages within-firm variation only, and therefore neglects the – possibly important – role of reallocation of market shares across firms in shaping aggregate mark-ups, as pointed out in De Loecker et al. (2020). This is consistent with the main purpose of the analysis in this section, i.e., to establish a robust link between development of digital technologies by firms and the increase in the mark-ups they can charge.

We find that the positive correlation between mark-ups and digital intensity is mainly driven by the intangible component of the digital transformation, and in particular by software investment and patenting in ICT-related technologies.

Intangible assets are an increasingly important component of economic activity, and especially ICT-related intangible assets (e.g., Brynjolfsson and Hitt, 2000; Brynjolfsson et al., 2002; Tambe et al., 2012). They are less excludable and more readily scalable than physical capital (Haskel and Westlake, 2017). Their limited excludability implies that ownership may be more contractual, and require patent, copyright or trademark protection, which can in turn translate into higher mark-ups for intangible-intensive firms (Bessen, 2020; Crouzet and Eberly, 2019). Scalability relates instead to the possibility to use these assets multiple times at low or zero marginal cost, as is the case for investment in software and in e-commerce capabilities. Furthermore, the development or adoption of software and e-commerce technologies can require a large initial fixed cost, which can be compounded by the need for complementary organisational investments, such as changes in business processes and work practices (Brynjolfsson and Hitt, 2000; Brynjolfsson et al., 2020 and 2021). While the rapid fall in the quality-adjusted price of information technology and intangible capital, such as software, can facilitate access to digital technologies across the board, the large overhead cost component of adoption gives large firms an advantage (Lashkari et al., 2019).

All these properties allow for economies of scale and provide an inherent advantage to companies which are able to leverage a given investment over higher sales and larger markets. This, in turn, can translate into higher mark-ups, insofar as intangible-intensive companies enjoy decreasing average costs and near zero marginal costs, but are shielded from the pressure of competitors to lower their prices to pass this through to customers. Indeed, when firms are exposed to global competition via e-commerce, our results suggest that they earn lower mark-ups on average. Firms operating in industries which make intensive use of e-commerce earn lower mark-ups on average, as the intense competition of operating on the global market, greater price transparency or ability of their customers to switch sellers more than compensates for any extra margin firms may enjoy from potential economies of scale. Indeed, we find that firm mark-ups are lower in industries with a large fraction of sales carried online, everything else held constant, and that this result is driven by firms in manufacturing industries.

High mark-ups following the adoption of digital technologies due to stronger reliance on intangible assets can therefore stem from the significant wedge between prices and near zero marginal costs combined with higher fixed costs, or the protection granted to some intangible assets by IP protection. Given the relevance of this argument, we investigate the importance of fixed costs in explaining the relationship between digital technologies and mark-ups. We estimate firm fixed costs following De Ridder (2019), and aggregate information at the industry level to minimise reverse causality concerns. We find that there is indeed a positive correlation between changes in firm mark-ups and the fixed cost intensity of production technologies, and that controlling for it does not significantly weaken the positive link between mark-ups and the development or use of digital intangible assets (e.g., software and ICT patents). This suggests that the contribution of intangible assets to within-firm mark-up growth does not only stem from the large upfront costs characterising the investment in such assets. Moreover, when we consider possible differences between manufacturing and service industries, we find that for service firms both software investment intensity is positively and significantly correlated with mark-ups, but not for manufacturing firms. The inverse is true for patenting. We further provide evidence that firms at the productivity frontier, the so-called "superstar" firms, can better translate efficiency gains into mark-ups than laggard firms. Moreover, if it is true that both laggard and frontier firms earn a mark-up premium from investing in software, this premium is much larger for frontier firms. This does not seem to be driven by these firms' ability to defend their investment strategically or acquire them externally through patents.

We test the robustness of our baseline results against other mechanisms that can affect firm mark-ups. First, we look at the role of international trade. Firm pricing strategies and mark-ups certainly can be affected by the number of direct competitors the firm faces. At the same time, larger markets allow for economies of scale, and enhance the benefits of intangible assets, as the same asset can be exploited to serve a larger number of customers at low marginal cost. When we augment our empirical model with measures of the exposure of industries to international trade, we find that firms operating in more open industries enjoy (weakly) lower mark-ups, mostly driven global import competition, suggesting the role of substitution effects on output prices.

Second, we explore the role of policies and in particular the pervasiveness of regulatory barriers and its role for mark-ups dynamics. Firms in highly regulated industries, where barriers to entry are high and competition among incumbents limited, can enjoy positive rents and charge higher mark-ups. We measure an industry's exposure to regulatory barriers with an indicator of Product Market Regulation in network industries - electricity, gas, telecom, post and air, rail and road transports - and in retail and professional services, and estimate the association of regulation to mark-ups of firms operating in all downstream industries which use the output of regulated industries as an intermediate input. We find that regulatory constraints in network industries decrease the mark-ups of firms operating in downstream industries, as they increase the marginal cost of production in those industries. Most importantly, however, the positive association between mark-ups and the intangible asset intensity of industries continues to hold when adding these extra controls and is not driven by the sample of firms producing in regulated industries.

Lastly, a growing number of studies uses different measures of market power instead, including concentration, firms' profits, return on investment or, for listed firms, dividends and market capitalisation.[3]

Several studies notably rely on output concentration in the industry (Autor et al., 2020; Bessen, 2020; Gutierrez and Philippon, 2017a,b, and 2018). Concentration could represent an important omitted variable in our empirical model, as it was found to correlate to both intangible assets (e.g., Crouzet and Eberly, 2019) and mark-ups (e.g., Hall, 2018). In a final specification, therefore, we estimate the main relationship of interest but with an extra control

[3] Autor et al. (2019), Bessen (2020), Gutierrez and Philippon, (2017a,b and 2018), and Grullon et al. (2019) provide evidence of an increase in product market concentration since the 1980s in the United States, based on either Economic Census data or data on publicly listed companies. Autor et al. (2020) further test a theoretical model where industries are characterised by "winner-takes-most" dynamics, and where the increased concentration of sales is linked to the decline of the labour shares and higher mark-ups. Gutierrez and Philippon (2018) show that the concentration has increased in the U.S. and decreased in Europe, while Bajgar et al. (2019) find a steady increase in European industry concentration between 2000 and 2014. Furman and Orszag (2018) claim that high returns on invested capital are indicative of the increased profitability of firms in the U.S. Barkai (2020) finds that the decrease in labour share of value added in the same country in the last 30 years was coupled to an increase in the profit share and not in the capital share. He also provides evidence that industries which experienced a larger decline in the labour shares between 1997 and 2012 also displayed a higher growth in product market concentration. Similarly, Grullon et al. (2019) highlight that profits increased the most in U.S. industries experiencing the most prominent rise in concentration.

for the industry's output concentration level, and more precisely the share of output produced by the largest 4 or 8 business groups operating in the industry (Bajgar et al., 2019). The two proxies of market power are found to be positively correlated. Most importantly, across the three mentioned exercises, the intangible-mark-up relationship continues to hold despite of the introduction of an extra set of controls.

Our study most closely relates to the literature on mark-ups. An increase in mark-ups is found in the U.S. by Hall (2018) using industry-level KLEMS data, and by De Loecker et al. (2019) using Compustat data. In particular, De Loecker et al. (2019) show that mark-ups have increased across all industries of the U.S. economy since the 1980s, driven by growth in high mark-up firms. They interpret this as evidence of increased market power and connect it to the decrease in the labour share, labour force participation and low-skill workers' wages.

We also contribute to the recent literature linking changes in business dynamics to investment in intangible assets, which has mostly focused on the U.S. with some more limited evidence for France. For the U.S., Crouzet and Eberly (2019) show that the rise in intangible investments is driven by industry leaders and coincides with increases in their market share, although with mixed result across industries. Bessen (2020) links the increase in concentration to the use of proprietary software. Brynjolfsson et al. (2008) find that ICT intensive industries in the U.S. have become more concentrated over time and account for the bulk of increased industry turbulence between the late 90s and early 2000s. Autor et al. (2020) provide evidence that the largest firms have gained the lion's share of industry sales thanks to technological change and integrated global markets. Two notable studies provide evidence for France. Lashkari et al. (2019) finds that rapid falls in quality-adjusted ICT prices can give larger firms - who can invest heavily in developing proprietary software - major advantages in logistics and inventory control management. De Ridder (2019) proposes a model where the rise of intangible inputs, by reducing marginal costs and endogenously raising fixed costs, can cause a slowdown of productivity growth.

We contribute to this literature by focusing on a specific trend, the increase in mark-ups, for a number of countries and by linking it for the first time to several different measures of the economy's digital transformation. Furthermore, our empirical exploration of the link between mark-ups and digital technologies accounts for a number of possible confounding factors, such as the role of fixed costs, the exposure to competition from foreign producers, and regulatory barriers to entry and competition.

Globally, all our results confirm the existence of a "mark-up premium" for firms operating in industries with important investments in digital technologies, proxied by investment in software, e-commerce capabilities, and ICT related patents. This is coherent with emerging evidence that recent spread of digital technologies seems to have benefitted disproportionately firms that invested heavily in intangible assets, and therefore face high fixed costs but also low marginal costs.

The rest of the paper is organised as follows. Section 2 describes the methodology adopted to estimate mark-ups. Section 3 describes the dataset used, including the definition of digital industries. Section 4 presents results on the evolution of mark-ups over time and how mark-ups differ between industries according to their digital intensity. Section 5 investigates which features of technology are driving the correlation between digital technology and mark-ups, including the industry's fixed cost intensity and firm's standing relative to the frontier of TFP. Section 6 explores the role of three alternative explanations for the evolution of mark-ups, namely international competition, product market regulation and industry concentration, and proposes a host of robustness checks on the baseline specification. Section 7 concludes.

2. Mark-up estimation

We estimate firm mark-ups as proposed in the work of De Loecker and Warzynski (2012), that builds on Hall (1988). Mark-up is defined as the ratio between output price, P_{it}, over its marginal cost, c_{it}. In this framework, mark-up is derived from the first order conditions with respect to the flexible input of the firm's Lagrangian function associated to the cost minimisation problem, and corresponds to the ratio between the elasticity of output with respect to the flexible input, OE_{it}^{m}, and the cost of the variable input as a share of the firm's revenue, IS_{it}^{m}. For further details on the derivation of the expression for mark-ups, see Annex A. Therefore, mark-ups are given by:

$$\mu_{it} = \frac{P_{it}}{c_{it}} = \frac{OE_{it}^{m}}{IS_{it}^{m}}. \tag{1}$$

We assume intermediates (as opposed to labour) to be flexible inputs. The assumption of a fully flexible input seems, indeed, more realistic for intermediate goods and services than for labour, especially in consideration of labour market rigidities (e.g., firing costs) that characterise some countries relatively more than others in the sample.

To estimate the elasticity of output with respect to intermediates, we consider two specifications for the firm-specific production function, both based on gross output and three inputs (labour, capital, and intermediates): a Cobb-Douglas (2) and a Translog production function (3), that for a given firm *i* can be written. For a given firm *i*:

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it} \tag{2}$$

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{ll} l^2{}_{it} + \beta_{mm} m^2{}_{it} + \beta_{kk} k^2{}_{it} + \beta_{lm} l_{it} m_{it} + \beta_{lk} l_{it} k_{it} + \beta_{mk} m_{it} k_{it} + \omega_{it} + \varepsilon_{it} \tag{3}$$

where y_{it} is the log of deflated firm gross output, and l_{it}, m_{it}, k_{it} are, respectively, (log) labour, intermediates, and, capital, while ω_{it} is firm productivity, and ε_{it} is the error term. The output elasticity of interest is given by the first derivative of (2) and (3) with respect to the intermediate input. While both production functions have strengths and weaknesses when used to estimate mark-ups, estimates via the Cobb-Douglas are generally considered more stable in the literature than those obtained through the Translog. Therefore, our baseline results will be based on the Cobb-Douglas production function, and we will use results based on the Translog production function as robustness.

In order to control for simultaneity and selection bias, we follow the literature and rely on a control function approach to estimate econometrically the parameters of the production function, using the Ackerberg, Caves and Frazer (2015) (ACF) approach. We correct the expenditure share in intermediates for measurement error in output, as obtained in the first stage of the ACF procedure, as in De Loecker and Warzynski (2012).[4]

Our data does not contain separate information on "Selling, General and Administrative" expenses that would allow replicating De Loecker and Eeckhout (2018b) correction in response to Traina (2018). For robustness we rely instead on the extensive testing of the production approach under different assumptions (e.g., Cobb-Douglas vs Translog) and on a control for the fixed cost intensity of production in our baseline econometric specification.

Given an estimate of firm mark-ups, we can also approximate firm-level fixed cost of production, following De Ridder (2019):

$$\mathrm{F}_{it} = \left(1 - \frac{1}{\mu_{it}}\right) \cdot P_{it}\,\mathrm{y}_{it} - \pi_{it}, \tag{4}$$

where μ_{it} is the mark-up of firm i at time t, $P_{it}\,\mathrm{y}_{it}$ are firm revenues, and π_{it} are firm operating profits (defined as operating income minus operating expenses).

3. Data and descriptive statistics

3.1. Firm-level date to compute mark-ups

The firm-level data necessary to compute firm mark-ups are sourced from the commercial dataset Orbis® by Bureau van Dijk (BVD). The sample used covers the period 2001-2014 for 25 countries: Australia, Austria, Belgium, Bulgaria, Denmark, Estonia, France, Finland, Hungary, Germany, Indonesia, India, Ireland, Italy, Japan, Republic of Korea, Luxembourg, the Netherlands, Portugal, Romania, Slovenia, Spain, Sweden, the United Kingdom, and United States.

[4] We estimate the production functions separately in each 3-digit industry. We remove observations for which the estimated mark-up was lower than 1 and, as standard in literature, we drop the top and bottom 3% of the distribution of mark-ups, in order to sure be that the estimates are not affected by outliers.

A number of steps are required to make the dataset suitable for economic analysis, including ensuring comparability of nominal values across years and countries (by deflating with industry-level PPP) and cleaning to net out the influence of measurement error and extreme values in the analysis.[5] To limit concerns over the representativeness of the dataset, we include in the analysis only firms employing on average at least 20 workers over the period, following Bajgar et al. (2020). As Orbis reports mostly consolidated data for U.S. firms and both consolidated and unconsolidated data for European ones, we only exploit consolidated data to enhance comparability in the cross-country analysis. The final sample was further restricted to industries for which firm multi-factor productivity can be estimated using the reported financial information (manufacturing and non-financial market service sector firms excluding utilities (ISIC rev. 4 industries 35 to 39), construction (41 to 43), and real estate activities (68). Lastly, Orbis does not report data on technologies adopted by firms. We therefore resort to using two additional sources of information: an indicator of the digital intensity of industries, and data on ICT patents filed by the firms in the sample.

3.2. The digital intensity of industries

As the digital transformation unfolds, it affects industries differently, depending on their rate of adoption of the new technologies and business practices. Recent work by Calvino et al. (2018) benchmarks 36 ISIC rev. 4 industries by their degree of digital intensity over the period 2001-2015. It looks at the digital transformation in its various manifestations, and in particular its technological components (the volume of software and ICT tangible investment over total investment, purchases of intermediate ICT goods and services over total output, robot stock intensity), the human capital it requires to embed technology in production (ICT skills, or the proportion of an industry's workforce employed in ICT-specialist occupations), and the way it changes the interface of firms with the output market (online market access, or the proportion of an industry's sales carried out online).[6] Each industry gets attributed a single value across all the considered dimensions then ranked, and the resulting distribution divided in quartiles.

[5] Negative values for gross output, value added, labour and intermediates were removed. The 1% tails of the distributions of the same variables were also removed, as well as the industries with less than 500 observations over the whole period.

[6] In the econometric analysis further below, we drop robot stock intensity, as this is only available for manufacturing industries and would thus excessively reduce the sample of analysis.

This is done for the end period of the sample (2013-15) and for the starting period (2001-03). Table A.1 displays this single ranking for the industries included in the paper in both periods.

3.3. Matched firms' financial accounts and patent data

Patents approximate a firm's ability to produce technological innovations. They protect the outcome of the invention process, which displays two fundamental features of interest for the analysis: it requires a large intangible investment (usually recorded as R&D investment) and implies important fixed costs. They further provide a regulatory barrier to competitors, thus generating rents from the innovation process. Importantly, information on patents can be linked to the firms that produced them.

The OECD Patent Database covers all patents filed at European Patent Office (EPO) and through the PCT system since 1978, patents granted by the US Patent and Trademark Office (USPTO) since 1976, and patents belonging to IP5 patent families. As no numeric firm identifier is available in patent documents, patents were attributed to firms in Orbis on the basis of the assignees' names, using an algorithm that minimised discrepancies between the names reported in the two datasets, as in Squicciarini and Dernis (2013). To ensure comparability and avoid double counting, the analysis use patent families rather than patents, i.e., it considers all patents originating from the same inventive steps and priority patent as one.[7]

Among all patent families filed by the company, we are particularly interested in the sub-sample of those that are ICT related. Patents are allocated to technology fields using International Patent Classification (IPC) codes, following the classification presented in Schmoch (2008, revised in 2013). For the purpose of this study, patent families are labelled as ICT-related if they fall in technology fields 1 to 8.[8]

The main indicator used in the analysis is the stock of ICT-related patents as a share of output. The stock of patents assigned to the firm in a given year is calculated as the sum of the depreciated patent count since the year of first filing of the first patent. The depreciation rate is

[7] In the continuation of this paper, "patent" and "patent family" are used interchangeably.

[8] In a robustness specification, we also use an alternative definition of ICT patents, which relies on more fine-grained technology classes, as developed by Inaba and Squicciarini (2017), and find quantitatively and qualitatively very similar results.

set to 15%, as in Hall et al. (2005). In a robustness specification, we also construct a quality-weighted patent stock intensity indicator, where the average "quality" of the patents attributed to the firm is measured by forward citations (citations a patent receives from subsequent patents) and serves as a proxy of the technological importance of the patented invention.[9]

3.4. Additional data sources

To account for possible explanations of firm mark-ups alternative to digital technology diffusion, we first collect information on an industry's trade openness to international trade in goods(sum of all imports and exports by the industry's output). We further distinguish between imports and exports, and between intermediate and final products. Data are sourced from the OECD Inter-Country Input-Output tables, at the industry-country-year level.

The degree of competition existing in a market affects a firm's pricing strategy (through direct competition on the product market) and/or cost structure (for firms protecting their market shares through improvements in the production technology or the quality of output – e.g., Bloom, Draca and Van Reenen, 2015). While measuring the degree of competition in the market directly may be difficult, our analysis accounts for the pervasiveness of regulatory barriers in the industry, which in turn might affect competition. For this purpose, we rely on the indicator for Product Market Regulation (PMR) in network industries - electricity, gas, telecom, post and air, rail and road transports - and in retail and professional services (Koske et al., 2015, and Duval et al., 2018). We then feed information on PMR in these industries into an input-output matrix and measure how intensively a downstream industry relies on the inputs produced by the regulated upstream industries. The resulting indicator measures how anti-competitive regulation in input markets affects production in downstream output industries (see for a similar approach e.g., Arnold, Javorcik and Mattoo, 2011).

Lastly, we source information on the degree of concentration of industries from Bajgar et al. (2019). These authors estimate the share of 4 and 8 largest business groups (CR4, CR8) in

[9] The number of citations of a given patent is calculated over a 5-year window after filing, and is likely to be therefore underestimated for patents filed after 2010, due to truncation in the accessed dataset. The number of citations is normalised, i.e., divided by the average number of citations received by other patents in the same technological field and year. We focus on "X" and "Y" citations, which identify a patent of higher technological value (Squicciarini et al., 2013).

the sales of an industry-country in a given year, approximately at the 2-digit ISIC4 aggregation level, using both Orbis and National Accounts data. The resulting data is restricted to countries with good and stable coverage in Orbis between 2002 and 2014 and is therefore available for a smaller number of countries than in the main analysis (Belgium, Finland, France, Hungary, Italy, Japan, Korea, Slovenia, Spain, Sweden, the United Kingdom, and the United States).

4. The evolution of mark-ups and digital intensity

In this section we report trends in firm level mark-ups over the period 2001-2014 across 25 countries, as unweighted average log mark-ups (Figure 1).[10] The figure shows that mark-ups have been increasing by around 8% (4%) between 2001 and 2014 when using a Cobb-Douglas (Translog) production function. A similar increase is also reported in a recent study by De Loecker et al. (2020), who estimate mark-ups over a longer time horizon for publicly traded companies in the United States. Reassuringly, the two production functions exhibit similar patterns over time.

Figure 2 plots instead the average percentage changes in mark-ups for the top, the bottom and the median decile of the mark-ups distribution.[11] While the bottom decile exhibit a flat trend, the top decile increases over time by more than 2 times the average (and median) mark-up. Furthermore, once firms are grouped by their mark-up levels, the average growth in mark-ups appears to be mainly driven by those firms that enjoy the highest level of mark-ups (i.e., firms in the top decile of the mark-up distribution). Stated differently, it is firms in the top half of the distribution, and in particular firms with the highest levels of mark-ups, that increasingly enjoy larger mark-ups vis-à-vis firms belonging to bottom half of the mark-up distribution. The results are consistent with De Locker and Eeckhout (2017), but expands on them by looking at all firms (as opposed to listed firms), and for various countries (as opposed to the U.S. only). A further robustness specification (Figure A 1) estimates year dummies of a panel-data

[10] We aggregate using unweighted averages because the sample at our disposal is not representative of the whole population of firms in a country, and coverage is rather heterogeneous across countries. Using market share weights, as in De Loecker et al. (2020), would not solve this issue but rather exacerbate it. We are reassured by De Loecker et al. (2020), who provide evidence that the increase in the unweighted series of mark-ups was lower than that of the weighted ones in the U.S. If anything, therefore, we may be underestimating the increase in average mark-ups over the period.

[11] Firms are divided into 10 deciles over the mark-up distribution in each 2-digit industry-year.

regression of average log mark-ups, controlling for country fixed effects, and retrieves increasing mark-ups over time even when controlling for country-specific aggregate shocks. Lastly, Table A.2 of Annex C treat manufacturing and non-financial market service sectors separately. Mark-ups growth is on average higher in the services sector and mark-up growth higher in services.

In sum, looking at trends of mark-ups over time, we have shown that: i) on average, mark-ups are increasing over the period 2001-2014; ii) growth is driven by those firms belonging to the top half of the mark-up distribution, the bottom half exhibiting essentially a flat trend over time; iii) mark-ups are on average higher in the non-financial market service sector than in manufacturing, although they have been growing in both sectors.

4.1. Link between mark-ups and the digital intensity

Table 1 reports selected summary statistics dividing the sample into digital intensive and less digital intensive industries, for the two periods for which the digital dummy is available (2001-2003 and 2013-2014). All means are statistically different across samples (two-sided t-test).

In particular, firms operating in industries defined as digital intensive at the beginning of the period (top-right quadrant of the table) display on average higher mark-ups not only with respect to firms in non-digital industries at the beginning of the period (top left quadrant of the table), but also at the end of the period (bottom right quadrant of the table). In addition, firms operating in digital intensive industries exhibit higher average growth in mark-ups than firms operating in less digital intensive industries.

In order to account for other factors that differ across digital intensive and less digital intensive industries, and which are related to mark-ups themselves, we estimate the following model:

$$\ln(\mu)_{i,j,t} = \alpha_0 + \alpha_1 DigInd_{j,T} + \mathbf{X'}_{\mathbf{i,j,t-1}}\boldsymbol{\beta} + \rho_{c,t} + u_{i,j,t} \quad (5)$$

for firm i in industry j, country c, at time t, where t is one of the years in T= {(2001-2003); (2013-15)}. The country subscript was omitted for all terms (except for $\rho_{c,t}$) for simplicity.

The dependent variable is the log of mark-ups. The dummy variable *DigInd* indicates whether the firm i operates in a digital intensive industry. 2-digit ISIC rev.4 industries are defined as digital intensive if they display a higher digital intensity than the median among all 36 industries considered (across countries) in one of the years covered by the indicator in one of two periods (2001-03 and 2013-15).

The vector $\boldsymbol{X}$ includes additional covariates at the firm level, namely the firm's age, capital intensity (as proxied by capital stocks over nominal output) and, in robustness specifications, MFP. Fixed effects for country-year pairs ($\rho_{c,t}$) are also included, so as to control for country specific time varying aggregate shocks. All specifications are estimated by pooled OLS, with standard errors clustered at the firm level or, in robustness specifications, at the country-industry level.

Figure 3 plots differences in mark-ups for firms operating in digital intensive industries relative to less digital intensive industries conditional on other firm characteristics, such as age, capital intensity, productivity, and country-year of operation. Industries are classified as "digital", if their digital intensity is above the median of all industries , and as "top-digital" if they are in the top quartile of the industry distribution in terms of digital intensity. A table with the same estimated results is reported in the online Annex D for completeness (Table A.2).

Two main results emerge: first, firms in the high-digital industries are found to display on average higher mark-ups than firms operating in the low-digital ones, everything else held constant. The estimates suggest that firms operating in a "digital intensive" industry enjoy a 15 to 20%[12] higher mark-up than firms operating in less digital intensive industries, and that this gain is substantially higher (up to 60%) if a firm is operating in one of the top digital industries. Such a result could reflect both changes in production as a consequence of the digital transformation (e.g., stronger reliance on intangible assets and higher fixed costs), and a shift in the market structure, as lower costs of production, easier penetration of several markets, network effects and higher intensity in knowledge assets allow digital companies to scale up faster and more easily, and to generate increasing returns to scale. Second, the gap in mark-ups between the average firm in a high-digital vs. low-digital intensive industry is larger in 2013-2014 than in 2001-2003, suggesting that the digital gap has increased over time and is stronger nowadays than in the past.

[1212] 20%=exp(0.188)-1. See Halvorsen and Palmquist (1980).

We confirm the robustness of the baseline results by: i) clustering errors at the country-industry level (as clustering at the industry level only would leave us with too few clusters); ii) using as dependent variable the estimates of mark-ups obtained when assuming a Translog production function instead of a Cobb-Douglas; iii) fixing the digital intensity classification to the first period and performing the regressions on the whole period (2001-2014); iv) conditioning the sample to be the same for the Cobb-Douglas and the Translog case; v) conditioning the sample to G20 vs. non-G20 countries; vi) conditioning the sample to all non-US firms; vii) using the top decile instead of the top quartile of industries. Robustness checks on i), ii) and iii) are reported, in Annex D, while the others are omitted for brevity and are available on request.

We then distinguish between digital manufacturing and market service firms (Table A.6). First, firms operating in the services sector, even in less-digital ones, display higher mark-ups than firms operating in manufacturing. Second, the correlation between digital intensity and mark-ups is stronger in services than in manufacturing. Third, within the services sector, the correlation is much stronger for firms operating in digital intensive industries. Lastly, differentials in mark-ups between firms in digital vs. less digital industries have increased over time, both in services and manufacturing sectors. One explanation for these differences is the intangibility of services relative to manufacturing: a firm producing software has high fixed costs, but it is also able to scale up at near zero marginal costs, contrary to a firm that produces ICT hardware in the manufacturing sector, that never faces zero marginal costs when producing more hardware. We test the soundness of this explanation (and alternative ones) in the next sections.

These associations, however, cannot be interpreted causally. If higher mark-ups generate higher profits, and if firms' investment is at least partially funded through cash flows, firms with higher mark-ups may be more digital intensive because they can afford the investment in new technologies. Concerns about the endogeneity of technology in Figure 3 are lessened using industry-level rather than firm-level information. Moreover, we exploit multiple dimensions of the digital transformation, some of which do not require large market power or profits to be acquired (e.g., the hiring of an ICT specialist).

5. The intangible components of digital matter the most for mark-ups

We further investigate the proposed correlation between mark-ups and digital intensity of industries by exploiting the full available variation in the data across countries, industries, and years, while accounting for heterogeneity across firms in the framework of a within-firm analysis. We estimate:

$$\ln(\mu)_{i,j,c,t} = \alpha_0 + \boldsymbol{X'}_{\boldsymbol{i,j,c,t-1}}\boldsymbol{\beta} + \boldsymbol{Z'}_{\boldsymbol{j,c,t-1}}\boldsymbol{\delta} + \rho_{c,t} + \vartheta_{j,t} + \gamma_i + u_{i,j,c,t} \qquad (6)$$

where all variables in common with equation (5) keep the same meaning, $\vartheta_{j,t}$ are sector-year (where sector: manufacturing or service) fixed effects, γ_i is a firm-specific dummy, and $\boldsymbol{X'}_{\boldsymbol{i,j,c,t-1}}$ are firm-specific controls (age, capital intensity). $\boldsymbol{Z'}_{\boldsymbol{j,c,t-1}}$ stands for different technology proxies of the digital transformation that were used to produce the taxonomy of industries by digital intensity (as in Calvino et al., 2018, but exploiting the additional country variation), or the patent stock intensity (in which case, it should be written as $\boldsymbol{Z'}_{\boldsymbol{i,j,c,t-1}}$). They are lagged once to reduce the endogeneity bias due to reverse causality.

The specification in (6) dispels concerns over the existence of omitted variable bias due to unobserved, time-invariant characteristics of firms included in the analysis, and time-varying features of manufacturing vs service sectors. This does, however, come at some cost: the focus of the analysis is narrowed down to the dynamics of mark-ups *within* firms and neglects between-firm differences.[13] Moreover, the empirical identification of $\boldsymbol{\delta}$ can only rely on time-variation in the country-industry dimensions $\boldsymbol{Z'}$ within the manufacturing or service sectors of the economy.

We therefore test the hypothesis that mark-ups are higher in firms operating in digital intensive industries because these industries invest heavily in intangible assets. Intangible assets are more readily scalable and less excludable than physical capital (Haskel and Westlake, 2017). Their limited excludability implies that ownership may be more contractual, often requiring patent, copyright, or trademark protection, which can exclude competitors from using the assets and allow for higher prices of output. In Bessen (2020), for instance, proprietary ICT generates innovation that competing firms cannot access, thus creating quasi-rents similar to

[13] In particular, (industry-level) aggregate mark-ups can increase even when firm mark-ups decrease. This is of course due to a mechanism of reallocation of market shares from low-markup to high-markup firms if these are larger and more productive. If the skewedness across firms is sufficiently large, the reallocation effect can dominate (Van Reenen, 2018). The analysis that follows in this section does away with the reallocation channel to limit the extent of omitted variable bias in the within-firm estimations.

patents. At the same time, patents grant the exclusive use of the underlying inventions to the owner, which is equivalent to a barrier to entry (Covarrubias et al., 2020) and is expected to generate rents. Forms of contractual protection of intellectual property may be used strategically to shield firms from competitors, especially where the pace of technological development is especially rapid (Abrams et al., 2013).

High fixed costs, low marginal costs, frequent spillovers and complementarities with other assets translate into large investments in the development and maintenance of intangible assets, but minimal additional costs of using these intangible assets when production is scaled up (Haskel and Westlake, 2017). This, in turn, can generate large mark-ups, if low marginal costs allow for faster scale-up and there is no equivalent reduction in output prices. This is especially relevant in the context of the digital transformation: a given software, for instance, can be used in many different contexts at low (often near zero) marginal costs. This advantage can further lower the cost of entry and operating in multiple markets at the same time, which can result in higher mark-ups and more concentrated markets for the most efficient firms (Aghion et al., 2019). At the same time, intangible assets require large initial investments, both in the assets themselves, and into complementary organizational assets such as business processes (Brynjolfsson and Hitt, 2000), and especially in the case of ICT (Brynjolfsson, 2020). Overhead costs linked to reorganisation for technology adoption give large firms an advantage, as the costs can be spread over larger output (Lashkari et al, 2019), so much so that these investments can become de-facto barriers to entry for potential competitors (Crouzet and Eberly, 2019). The upfront fixed cost of intangible assets, therefore, can both translate into higher prices to finance the investment, and act as a barrier to entry for competitors (Autor et al., 2020).
Table 2 shows the results of estimating equation (6) when $\boldsymbol{Z'}_{\boldsymbol{j,t-1}}$ contains each component of the digital intensity dummy separately (Columns 1 to 6), and the indicator for firm patent stock intensity (column 7).[14] Columns 8 and 9 introduce all of them in the same regression. In all our specifications standard errors are clustered at the industry-country level, and independent variables standardised.

We find that mark-ups are positively and significantly correlated with several types of intangible assets, such as the firm's intensity in ICT-related patents and the industry's intensity

[14] Table A.7 in Annex E describes these technology proxies as well as other explanatory variables of interest for the econometric analysis, conditional on the sample used where the regressors of the most demanding specification are all simultaneously non-missing.

in software investment. The simultaneous inclusion of all proxies of technology in the same specification (Columns 8 and 9) leaves the magnitude of the correlations virtually unchanged. As we show in the next sessions, these relationships are robust to various changes in the baseline specification, and to the inclusion of several potential competing explanations. The conditional correlations between mark-ups and other sub-dimensions of digital intensity, conversely, are not statistically significant, and we will omit these regressors from all future specifications as a consequence.

These results provide empirical backing for our main operating hypothesis: everything else held constant, the positive correlation between mark-ups and digital intensity is mainly explained by investment in selected ICT-related intangible assets. Indeed, intangible assets have certain defining features that are likely to translate into higher mark-ups, such as high fixed costs, low marginal costs, and limited excludability against which the legislator recognises some form of contractual protection.

We then explore whether the returns of such intangible investment are solely driven by the fact that these assets have a large fixed cost component. We therefore augment (6) with a control for the fixed cost structure of the industry where the firm operates. While the cost indicator in De Ridder (2019) is firm-specific, it is also based on the estimated mark-ups that are our dependent variable. To minimise endogeneity concerns, we aggregate fixed costs at the industry level averaging the estimated fixed costs within each country-industry and excluding the one to which the firm belongs in three different ways.[15] Column 11 shows that mark-ups are positively correlated to the measure fixed costs, as expected. More importantly, the positive correlation between mark-ups and software intensity, online market access or innovation continues to be significant, also after taking into consideration the fixed costs associated with the investment. This suggests that the contribution of changes in intangible assets to within-firm changes in mark-up does not only stem from the importance of fixed costs in intangible asset investment. As sketched before, a key property of intangible assets is their scalability, i.e., the fact that they can be replicated at close to zero marginal cost (Haskel and Westlake, 2017). This in turn can result in higher mark-ups, insofar as intangible-intensive companies enjoy decreasing average costs and minimal marginal costs, but do not feel the pressure of

[15] Results are robust to alternative aggregations such as averaging the estimated fixed costs in the top quartile of the distribution in each country-industry (which conservatively overestimates the importance of fixed costs in the empirical specification), or averaging the estimated fixed costs in each country-industry.

competitors to lower prices equivalently. Similarly, the persistence of a negative sign on the term of online market access intensity while controlling for the fixed cost structure of the industry strengthens the intuition that the coefficient on online market access captures the effect of global market competition on firm mark-ups.

As in the previous section, we further uncover that the relationship between intangible investment intensity and firm mark-ups holds differently for firms in manufacturing and services sectors (Table A.8 in Annex E): everything else held constant, the mark-ups return on the investment in software is higher in service than manufacturing industries. For patenting activities in ICT, conversely, the conditional estimates are broadly comparable between manufacturing and service industries.[16]

5.1. Mark-ups and technology in frontier vs non-frontier firms

Current markets are characterised by important skewedness in productivity (e.g., Andrews et al., 2016), similar to what we report for mark-ups in Section 4 Such skewedness in revenues and productivity in the context of imperfectly competitive markets can result in rising concentration of market shares in "superstar" firms that are both more efficient and more profitable (Autor et al., 2020).[17] Several changes in factor markets may enable this joint increase in efficiency and market power: the rising importance of scale economies, network effects or changes in consumers' ability to price-discriminate. Korinek and Ng (2017) argue that the digital transformation is at the root of many such changes, as it reduces costs for producers and allows for a positive cycle of innovation. For Crouzet and Eberly (2018), better productivity outcomes in retail firms are driven by firms' more extensive investment in intangible assets. Crouzet and Eberly (2019) find that growth in intangible assets is positively associated to productivity gains in some industries, and increases in mark-ups in others. A large literature provides empirical evidence that productivity gains from ICT investment materialise themselves thanks to complementary investments in skills or managerial practices (e.g., Caroli and Van Reenen, 2001; Bresnahan et al., 2002). All this evidence suggests that the relationship

[16] The results are not exclusively driven by the subsample of wholesale and retail traders, nor by that of knowledge-intensive industries.
[17] In this environment, changes in productivity and revenue concentration should be positively correlated. Gutiérrez and Philippon (2017a) and Covarrubias et al. (2020), however, find that correlation to be positive for the 1997-2002 period but not afterwards, while Gutiérrez and Philippon (2019b) find that the contribution of superstar firms to overall productivity growth has decreased over time.

between intangible investment intensity and firm mark-ups we focus on may be driven by firms' efficiency instead, and our estimates biased by the omission of one such control.

In this subsection we therefore estimate a term for the firm's position in the distribution of MFP. "Frontier" is a dummy variable which takes value 1 if the firm belongs to the top quartile of the MFP distribution of the same country, industry and year, and 0 otherwise (columns 1-2), or to the top 10 percentiles of the MFP distribution (columns 3-4).[18] First, our results exclude that our main variables of interest are simply capturing the underlying association between firms' mark-ups and efficiency, as the association of intangible investment to mark-ups can be found for both laggard and frontier firms (Table 3). Secondly, becoming a "frontier" productivity firm is associated to higher mark-ups, everything else held constant. Lastly, the most efficient firms enjoy greater returns from operating in industries that invest more in software, but not from innovating more in ICT, nor from operating in online markets. The result on software is consistent with the idea that intangible assets compound the advantages of top efficiency and allow leading firms to further expand their profits and market shares (e.g., Autor et al., 2020; Crouzet and Eberly, 2019).

6. Alternative explanations for the evolution of mark-ups

In this section we explore other competing explanations of mark-up dynamics, and how omitting these measures from the empirical model can affect the positive correlation between mark-ups and digital technology proxies. A battery of robustness checks for the baseline specification concludes the section.

6.1. International competition

A large theoretical literature (see Feenstra and Weinstein, 2017, for instance, for a review), has shown how international trade can simultaneously affect prices and marginal costs. On the one hand, competition from cheaper or better foreign products can decrease final goods' prices in the domestic market, or increase the quality (and, possibly, the price) of local products to escape competition. On the other hand, foreign competition can pressure local producers to modify

[18] A robustness specification estimating the baseline with an additional control for log-MFP is presented in the robustness Table 11. The use of a non-linear form in this section aims to minimize concerns of a "mechanical" positive correlation between MFP and mark-ups, which are both calculated from the same primitives.

production and improve their efficiency (lower X-inefficiencies), and decrease the marginal costs of production. Cheaper inputs make for cheaper outputs, or they can lower the cost of production and entry for domestic producers. If foreign inputs embody technological advancements, they can also affect the marginal cost of production in the domestic market. The relative importance of these effect on the magnitude of mark-ups – or even the existence of mark-ups altogether in the model – depends on the functional form of demand, and the preference for a monopolistic vs. oligopolistic competition set-up.

The empirical literature is equally substantial. Tybout (2003) reviews early studies and finds that the effect of import competition on local producers' mark-ups is overwhelmingly negative, especially for large companies. Similar results are found by a strand of literature focusing on anti-dumping protections and mark-ups of domestic firms (e.g., Konings and Vandenbussche, 2005). More recently, Edmond et al. (2015) provide evidence that productivity differentials between foreign and local market determine the sign of the change in mark-ups after trade liberalisation: if differentials are small, liberalisation exposes domestic producers to competition and reduces their mark-ups. Conversely, if productivities are different across borders, producers from one country can acquire larger market shares in the other country and increase mark-ups as a consequence. Amiti and Konings (2007) show that a decrease in input tariffs can raise the productivity of domestic producers, possibly by improving the quality of their output or inducing learning. De Loecker et al. (2016) find that the net effect of trade liberalisation of both input and output markets on the mark-ups of Indian final goods producers was actually positive. Output prices were depressed by a decrease in output tariffs, while lower input tariffs reduced the marginal costs of final goods producers, and much more than the elimination of X-inefficiencies from output competition. The result was a larger decrease in marginal costs than in output prices. Similarly, Bellone et al. (2016) find that the sign of import liberalisation on mark-ups is negative, but not for exporters, whose marginal cost decreases due to cheaper inputs, and mark-ups therefore increase. Lastly, in Meinen (2016), greater market penetration by Chinese producers is associated to lower mark-ups, but also to lower marginal costs when intermediate inputs are cheaper.

As per expectations, firms operating in industries with higher openness to trade enjoy lower mark-ups, but the correlation is hardly statistically significant unless a control for the fixed cost intensity of the industry is also included (Columns 1-2 vs 4-5, Table 4). Importantly, the simultaneous introduction of proxies for the industry's exposure to international trade leaves the elasticities of mark-ups to the three main technology correlates in the same ballpark as in the baseline specification. Moreover, a one standard deviation increase in the industry's trade openness is associated to 0.3% lower mark-ups for the firm, an effect which is three to four time lower than an equivalent increase in the industry's software investment intensity.

Columns 3 and 6 break down the openness term into its components, that may affect mark-ups differently according to previous literature: exports vs imports, imports of intermediate vs. final goods and services, and imports from China vs. the rest of the world. Firms operating in industries which are especially intensive in imports of final products from countries other than China ("rest of the world") enjoy significantly lower mark-ups, while this is not true for industries intensive in imports of final goods from China. The same estimation but neglecting the China – "rest of the world" split retrieves a negative correlation (evidence available on request). We interpret these results as evidence of an import substitution channel which decreases output prices and may force domestic firms to restructure and produce at lower marginal cost. For domestic producers of intermediate inputs, conversely, we find evidence that the marginal cost channel dominates the price channel, coherently with the idea that inputs of higher (resp. lower) technological content can decrease (resp. increase) marginal costs and raise (resp. decrease) mark-ups, which translates into different signs for the coefficients on imports from the Rest of the World vs China. The overall relationship between mark-ups and imports intensity of intermediate inputs is approximately zero, likely due to how different producers in the same industries pass changes in intermediate input prices through to final consumers. Lastly, the relationship between firm mark-ups and industries' export intensity is weak and suggests that the price at which the output is sold in the foreign market may not be sufficient to cover the increase in costs imposed by the exporting activity (as in, e.g., Bellone et al., 2016). The absence of a strong correlation to mark-ups can also reflect the existence of diverging competition and market size mechanisms (as in Aghion et al., 2018): many firms experience competition in the export market and therefore earn low mark-ups. For some selected – large and especially productive – firms, however, the scale effect of accessing larger markets may dominate, and translate in higher profits.[19]

[19] Lacking firm-level trade data, all the results in this section can only be interpreted in function of the average exporting firm in the industry despite the large existing heterogeneity in export prices within the same industry (e.g. Martin and Mayneris, 2015).

6.2. Product market regulation

Regulation and enforcement on conditions of entry ensure that firms compete on actual merits and market power does not perpetuate itself over time (Berry et al., 2019), but the regulator can decide to introduce barriers to entry per se, and some firms may be especially able to influence these decisions through lobbying. Entry regulations were found to reduce the creation of new firms (Laeven and Rajan, 2006; Gutiérrez et al., 2019a) and fostering entry reduces firm-level mark-ups, if not necessarily economy-wide ones (Edmond et al., 2022).[20]

Building on an indicator of Product Market Regulation (PMR) in network regulated industries - electricity, gas, telecom, post and air, rail and road transports - and in retail and professional services (Koske et al., 2015, and Duval et al., 2018) that captures barriers to entry of new firms in the industry and limits to the reallocation of market shares across incumbents, we create a first variable, "Upstream PMR", that quantifies the potential costs of the anti-competitive regulation on the input markets for the output of the industries which use such intermediate inputs. In other words, this variable measures the impact of regulatory barriers to competition in regulated industries across downstream industries that are characterised by different intensities in the use of inputs from regulated industries. A "Regulated" dummy, instead, identifies firms belonging to regulated industries themselves, so that the cross product of "Regulated" and "Upstream PMR" captures the direct link between regulatory barriers in regulated industries and mark-ups of firms operating in those very same industries.[21]

Table 5 shows the results of introducing this new control. First, the correlation between mark-ups and upstream PMR is negative and significant. Regulations in upstream industries (which produce services used as intermediates by others) increases marginal costs for the downstream industries, by reducing competition among incumbents and creating barriers to entry in industries providing intermediates, with a consequent negative effect on mark-ups. In regulated industries themselves (i.e., the coefficient on "Regulated #Upstream PMR" and "Upstream PMR" - Columns 4 and 5), this association is reduced and is tested to be insignificant; indeed, the limitations to entry and competition simultaneously affect firms' price

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[20] In Edmond et al. (2022), enhancing entry reduces the market share of small firms – which are more vulnerable to competition from entrants –in favour of large, high mark-up firms. The increase in market share of high mark-up firms keeps aggregate mark-ups almost unchanged despite a decrease in firm-level mark-ups.

[21] We cannot propose a direct test of the role of antitrust regulation and enforcement – which can also affect competition and price-cost margins (e.g. Grullon et al., 2019) – for lack of time-varying, industry-level comparable data on antitrust regulation or enforcement across countries.

of output (positively) and the cost of their intermediate inputs (negatively). Third, the existing associations of mark-ups with intangible investment continue to be significant, and their magnitude and significance are unaffected by the inclusion of the PMR term (Columns 2, 3), which suggests that the two relationships are mostly orthogonal. Fourth, we do not find a difference in the association of technology intensity to mark-ups between regulated and non-regulated industries (except when considering online market access intensity, which however does not hold when controlling for the industry's fixed cost intensity), which reassures us that the relationships of our main interest are not driven by the sample of regulated industries. Broadly these results further strengthen the message that firm mark-ups are the result of a complex system of firm and industry features, where the diffusion and adoption of digital intangible assets play an important role, and one which is not directly affected by regulation on barriers to entry.

6.3. The link with concentration

Recent studies also found that mark-ups are positively related to output concentration in the industry, too (Hall, 2018; Grullon et al., 2019; Covarrubias et al., 2020),[22] and that concentration is positively correlated to intangible investment (Akcigit and Ates, 2019b; Crouzet and Eberly, 2019; Autor et al., 2020; Bessen, 2020). To minimise concerns of omitted variable bias that would affect the coefficients on intangible investment and patents, we augment our empirical model with a control for concentration, while remaining conscious that the concentration-to-mark-up relationship is highly endogenous and cannot be interpreted causally (e.g., Berry et al., 2019).

Table 6 highlights that there is a non-linear relationship between concentration and mark-ups: changes in industry concentration are positively associated to changes in firm mark-ups, but only in industries that are characterised by lower levels of concentration. For firms operating in more concentrated industries, mark-ups are mostly uncorrelated with output concentration. Importantly, the magnitude and significance of coefficients for software, online market access and patents intensity stay approximately the same as in the baseline (Column 1).

[22] These studies consider the consequences of (changes in) industry concentration in a context where entry costs are high (or rising). That said, in a context where the elasticity of demand is also high, the market can sustain both higher concentration and higher competition at the same time.

6.4. Robustness

Lastly, Table 7 proposes a number of robustness exercises of the baseline specification (Column 1). Specifically in Column 2 we use an alternative indicator of patent intensity; we contrast all alternative explanations proposed above (with the exception of concentration) at the same time (Column 3); we augment the baseline model with a continuous measure for the firm's log-MFP and size (as measured by employment), respectively (Columns 4 and 5); in Column 6 we further control for the industry's R&D intensity, whereas in Column 7 we absorb all variation at the country-industry-year level, hence also the proxies of technologies which represent some of our main correlates of interest; lastly, in Column 8 we re-propose the baseline specification where firm mark-ups are estimated assuming a Translog production function, as mentioned in Section 3.1.In all the specifications we confirm positive and significant associations between firm mark-ups and software investment intensity and patent intensity, as well as a negative and significant association between firm mark-ups and online market access intensity, everything else held constant. The coefficients are also quite similar in magnitude across specifications. In particular, these robustness specifications show that our main results are not due to the omission of other potentially relevant factors, such as openness, PMR, fixed costs, MFP, size, R&D intensity and other digital technology proxies.

7. Conclusions

A growing body of literature has documented a number of empirical regularities over the past decades, including increases in mark-ups, concentration, profit dispersion and productivity divergence, a decline in business dynamism, and a slowdown in average productivity.

In this paper we focus on one of them, the increase in mark-ups, and expand the analysis to a larger set of countries (not only the U.S.) and to private (not only listed) firms relative to the literature. Thanks to the richness of a novel dataset which combines firm balance sheet data, patents, and industry-level measures of digital technology for 25 countries for the period 2001-2014, we document an increase in mark-ups over time, mainly driven by firms with the highest mark-ups.

Next, we look at the link between mark-ups and digital technologies, and the intangible component of those in particular. First, we show that mark-ups are higher in digital intensive industries than in less digitally intensive ones, and that this mark-up premium has increased over time. Second, when we investigate which features of the digital economy matter the most for mark-up dynamics, we document that the positive correlation between mark-ups and digital intensity is mainly driven by the intangible component of the digital transformation, after controlling for a number of other correlates of mark-ups and a demanding set of fixed effects. Firms operating in industries with higher levels of digital intangible assets and firms that develop and protect digital technologies, as proxied by their stock of ICT patents, enjoy indeed higher mark-ups.

The scalability of intangible assets corresponds to changes in the cost structure of production: firms need to invest in the development and maintenance of intangible inputs but face minimal additional costs of using these intangible assets when production is scaled up. In this scenario, high mark-ups following the adoption of digital technologies can reflect both the significant wedge between prices and near-zero marginal costs, and/or a higher fixed cost intensity of production in the industry. We find that – under our most demanding empirical specification – the contribution of intangible assets to firms' mark-up growth persists despite controlling for the fixed cost intensity of industries. In a similar way, we show that the same association is not driven solely by the sample of "superstar" firms, although frontier firms do enjoy an extra return (in mark-up terms) to investments in software.

Next, we explore three potential competing explanations for changes in mark-ups, namely the degree of openness to trade, exposure to regulatory barriers on the product market, and industry concentration. We document that these alternative phenomena play a role in explaining variations in mark-ups, but also that the extra controls do not affect the validity and magnitude of the correlations of mark-ups with software investment intensity, online market access intensity, and patent stock intensity.

Overall, all our results confirm the existence of a mark-up premium for firms operating in digital intensive industries, and in particular in industries characterised by high density in software investment and technological innovation as proxied by patents. Recent technological developments seem to have benefitted firms operating in intangible-intensive industries disproportionately. High fixed costs, coupled with low marginal costs and rising importance of investments in complementary assets, may deter competitors from entering the market, and grant higher mark-ups to large innovative incumbents. In industries that make intensive use of e-commerce, however, firms enjoy *lower* mark-ups on average, as this technology gives access to a larger, virtually global, market, but also increases the number of potential competitors and reduces output prices and margins as a consequence.

Our results more broadly support the view that technology adoption is an important driver of recent reported increases in market power. This does not diminish the relevance of other possible explanations of rising mark-ups in advanced economies, which we could not consider in our analysis. In particular, our results are not in contradiction to recent studies focusing on changes in antitrust regulation and enforcement as a source of corporate market power. Even if some firms attain their currently dominant positions on their merits by out-competing rivals, they may also start using their power to raise prices and restrict consumers' choices, entrenching their position by buying off possible rivals and lobbying for favorable regulatory conditions. In this economic scenario, it seems of utmost importance to understand how competition authorities can develop better tools to limit firms' market power and its adverse consequences on business sector innovation and growth.

References

Abrams, D.S., U. Akcigit, and J. Grennan (2013), "Patent Value and Citations: Creative Destruction or Strategic Disruption?", NBER Working Papers 19647.

Ackerberg, D., C. Lanier Benkard, S. Berry, and A. Pakes (2007), "Econometric Tools for Analyzing Market Outcomes", in: *Handbook of Econometrics*, ed. by J. Heckman and E. Leamer, Vol.6, pp. 4171–4276.

Ackerberg, D., K. Caves, and G. Frazer (2015), "Identification Properties of Recent Production Function Estimators", *Econometrica*, Vol.83, No. 6, pp. 2411–2451.

Aghion, P., A. Bergeaud, M. Lequien, and M.J. Melitz (2018), "The Heterogeneous Impact of Market Size on Innovation: Evidence from French Firm-Level Exports", NBER Working Papers 24600, National Bureau of Economic Research, Inc.

Aghion, P., A. Bergeaud, T. Boppart, P.J. Klenow, and H. Li (2019), "A Theory of Falling Growth and Rising Rents," NBER Working Papers 26448, National Bureau of Economic Research, Inc.

Akcigit, U., and Ates, S. T. (2021), "Ten facts on declining business dynamism and lessons from endogenous growth theory", *American Economic Journal: Macroeconomics*.

Akcigit, U., and Ates, S. T. (2019b), "What Happened to US Business Dynamism?", NBER Working Paper, No. 25756.

Amiti, M., and J. Konings (2007), "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia." *American Economic Review,* Vol. 97, No. 5, pp. 1611–1638.

Andrews, D., C. Criscuolo, and P. Gal (2016), "The best vs the rest: the global productivity slowdown, divergence across firms and the role of public policy", OECD Productivity Working Papers N. 5.

Arnold, J., B. Javorcik, and A. Mattoo (2011), "Does services liberalization benefit manufacturing firms? Evidence from the Czech Republic", *Journal of International Economics*, Vol. 85(1), pp. 136-146

Autor, D., D. Dorn, L.F. Katz, C. Patterson, and J. Van Reenen (2017), "Concentrating on the Fall of the Labor Share", *American Economic Review*, Vol.107, No. 5, pp. 180–185.

Autor, D., D. Dorn, L.F. Katz, C. Patterson, and J. Van Reenen (2019), "The fall of the Labor Share and the Rise of Superstar Firms", *The Quarterly Journal of Economics*, Vol. 135, No. 2, pp. 645–709.

Bajgar, M., G. Berlingieri, S. Calligaris, C. Criscuolo, and J. Timmis (2019), "Industry Concentration in Europe and North America", CEP Discussion Papers dp1654.

Bajgar, M., G. Berlingieri, S. Calligaris, C. Criscuolo, and J. Timmis (2020), "Coverage and representativeness of Orbis data", OECD Science, Technology and Industry Working Papers, No. 2020/6.

Bajgar, M., C. Criscuolo, and J. Timmis (2021), "Supersize Me: Intangibles and Industry Concentration", OECD Science, Technology and Industry Working Papers, No. 2021/12.

Barkai, S. (2020), "Declining Labor and Capital Shares", *Journal of Finance*, Volume 75, N.5, pp. 2421-2463

Bellone, F., P. Musso, L. Nesta, and F. Warzynski (2016), "International trade and firm-level markups when location and quality matter," *Journal of Economic Geography*, Vol.16, No. 1, pp. 67–91.

Berlingieri, G., P. Blanchenay, and C. Criscuolo (2017), "The Great Divergence(s)", OECD Science, Technology and Industry Policy Papers, No. 39.

Berry, S., M. Gaynor, and F. Scott Morton (2019), "Do Increasing Markups Matter? Lessons from Empirical Industrial Organization", *Journal of Economic Perspectives*, Vol.33, No. 3, pp. 44–68.

Bessen, J. E. (2020), "Information Technology and Industry Concentration", *The Journal of Law and Economics*, Vol. 63, No. 3, pp. 531-555.

Bessen J. E., E. Denk, J. Kim, and C. Righi (2020), "Declining Industrial Disruption", Boston University School of Law - Law & Economics Series Paper No. 20-28.

Bloom, N., M. Draca, and J. Van Reenen (2015), "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity", *The Review of Economic Studies*, Vol. 83(1), pp. 87–117.

Bresnahan, T., E. Brynjolfsson, and L.Hitt (2002), "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence", *The Quarterly Journal of Economics*, Vol. 117 (1), pp. 339-376,

Brynjolfsson, E., A. McAfee, M. Sorell, and F. Zhu (2008), "Scale without mass: business process replication and industry dynamics", Harvard Business School Technology & Operations Mgt. Unit Research Paper, No. 07-016.

Brynjolfsson, E., and Hitt, L. M. (2000), "Beyond computation: Information technology, organizational transformation and business performance", *Journal of Economic perspectives*, Vol.14, No. 4, pp. 23–48.

Brynjolfsson, E., D. Rock, and C. Syverson (2017), "Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics", *NBER Chapters*, in: The Economics of Artificial Intelligence: An Agenda, pp. 23-57, National Bureau of Economic Research, Inc.

Brynjolfsson, E., Hitt, L. M., and Yang, S. (2002), "Intangible assets: Computers and organizational capital", Brookings papers on economic activity, No. 1, pp. 137–181.

Brynjolfsson, E., Rock, D., and Syverson, C. (2021), "The productivity J-curve: How intangibles complement general purpose technologies" *American Economic Journal: Macroeconomics*.

Calvino, F., C. Criscuolo, L. Marcolin, and M. Squicciarini (2018), "A Taxonomy of Digital Intensive Sectors", OECD Science, Technology and Industry Working Papers, No. 2018/14.

Caroli, E. and J. Van Reenen (2001), "Skill-Biased Organizational Change? Evidence from A Panel of British and French Establishments", *The Quarterly Journal of Economics*, Vol. 116(4), pp. 1449-149

Corrado, C., C. Hulten, and D. Sichel (2005), "Measuring Capital and Technology: An Expanded Framework", NBER Chapters, in: *Measuring Capital in the New Economy*, pp. 11–46, National Bureau of Economic Research, Inc.

Covarrubias, M., G. Gutiérrez, and T. Philippon (2020), "From Good to Bad Concentration? U.S. Industries over the past 30 years*", NBER Macroeconomics Annual* 2020 34:, 1-46

Crouzet, N. and J. Eberly (2018), "Intangibles, investment, and efficiency". *AEA Papers and Proceedings*.

Crouzet, N., and Eberly, J. C. (2019), "Understanding weak capital investment: The role of market concentration and intangibles", NBER Working Paper, No. 25869.

De Loecker, J., and F. Warzynski (2012), "Mark-ups and Firm-Level Export Status", *American Economic Review*, Vol.102, No. 6, pp. 2437–71.

De Loecker, J., and J. Eeckhout (2018a), "Global market power", NBER Working Paper, No. 24768.

De Loecker, J., and J. Eeckhout (2018b), "Some Thoughts on the Debate about (Aggregate) Markups Measurement", unpublished.

De Loecker, J., J. Eeckhout, and G. Unger (2020), "The Rise of Market Power and the Macroeconomic Implications", *The Quarterly Journal of Economics*, Vol. 135, n.2, pp. 561-644.

De Loecker, J., P. K. Goldberg, A.K. Khandelwal, and N. Pavcnik (2016), "Prices, markups, and trade reform", *Econometrica*, Vol.84, No. 2, pp. 445–510.

De Ridder, M. (2019), "Market Power and Innovation in the Intangible Economy", Cambridge Working Papers in Economics 1931.

Decker, R. A., Haltiwanger, J., Jarmin, R. S., and Miranda, J. (2017), "Declining dynamism, allocative efficiency, and the productivity slowdown", *American Economic Review*, Vol. 107, No. 5, pp. 322–26.

Diez, F., D. Leigh, and S. Tambunlertchai (2018), "Global Market Power and its Macroeconomic Implications", IMF Working Paper, No. WP/18/137.

Duval, R.A., D. Furceri, B. Hu, J. Tovar Jalles, and H. Nguyen (2018), "A Narrative Database of Major Labor and Product Market Reforms in Advanced Economies", IMF Working Papers, No. 18/19.

Edmond, C., V. Midrigan, and D.Y. Xu (2015), "Competition, Markups, and the Gains from International Trade," *American Economic Review*, Vol. 105, No. 10, pp. 3183–3221.

Edmond, C., V. Midrigan, and D.Y. Xu (2022), "How Costly Are Markups?", *Journal of Political Economy*, forthcoming.

Feenstra, R.C. and D.E. Weinstein (2017), "Globalization, Markups, and US Welfare", *Journal of Political Economy*, Vol. 125, No.4, pp. 1040–1074.

Furman, J, and P. Orszag (2018), "A Firm-Level Perspective on the Role of Rents in the Rise in Inequality", in: Toward a Just Society, Columbia University Press.

Goldschlag, N. and A. Tabarrok (2018), "Is Regulation to Blame for the Decline in American Entrepreneurship?," *Economic Policy*, Vol.33 (93), pp. 5–44.

Griffith, R., R. Harrison, and H. Simpson (2006), "The link between product market reform, innovation and EU macroeconomic performance", European Economy - Economic Papers, No. 243.

Grullon, G., Y. Larkin, and R. Michaely (2019), "Are U.S. Industries Becoming More Concentrated?", *Review of Finance*, Vol. 23, No. 4, pp. 697–743.

Gutiérrez, G., and T. Philippon (2017a), “Declining Competition and Investment in the U.S.”, NBER Working Paper, No. 23583.

Gutiérrez, G., and T. Philippon (2017b), “Investment-less Growth: An Empirical Investigation”, Brookings Papers on Economic Activity, Fall 2017.

Gutiérrez, G., and T. Philippon (2018), “How EU Markets Became More Competitive Than US Markets: A Study of Institutional Drift”, NBER Working Paper, No. 24700.

Gutiérrez, G., J. Callum, and T. Philippon (2019a), “Entry Costs and the Macroeconomy,”, National Bureau of Economic Research Working Paper 25609.

Gutiérrez, G., and T. Philippon (2019b), “Fading Stars”, *AEA Papers and Proceedings*, Vol. 109, pp. 312-316.

Hall, B. H., and J. Mairesse (1995), “Exploring the Relationship Between R&D and Productivity in French Manufacturing Firms”, *Journal of Econometrics*, Vol.65, No. 1, pp. 263–293.

Hall, B. H., Jaffe, A., and Trajtenberg, M. (2005), “Market value and patent citations”, *RAND Journal of economics*, Vol.36, No. 1, pp.Vol. 36, No. 116–38.

Hall, R. E. (1988), “The relation between price and marginal cost in US industry”, *Journal of Political Economy*, Vol. 96, No. 5, pp. 921–947.

Hall, R. E. (2018), “New Evidence on the Markup of Prices over Marginal Costs and the Role of Mega-Firms in the US Economy”, NBER Working Paper, No. 24574.

Halvorsen, R., and Palmquist R. (1980), “The Interpretation of Dummy Variables in Semilogarithmic Equations”, *American Economic Review*, Vol.70, No. 3, pp. 474–475.

Haskel, J., and Westlake, S. (2017), *Capitalism without capital: the rise of the intangible economy*, Princeton University Press.

Hsieh, Chang–Tai and Peter J. Klenow. “Misallocation and manufacturing TFP in China and India”, *The Quarterly Journal of Economics*, Vol.124, No. 4, pp.1403–1448.

Inaba, T. and M. Squicciarini (2017), “ICT: A new taxonomy based on the international patent classification”, OECD Science, Technology and Industry Working Papers, No. 2017/01, OECD Publishing, Paris, https://doi.org/10.1787/ab16c396-en.

Jovanovic, B., and Rousseau, P. L. (2005), “General purpose technologies”, In: *Handbook of Economic Growth*, Vol. 1, Part B, pp. 1181–1224.

Luc Laeven, L., and R. Rajan (2006), “Entry Regulation as a Barrier to Entrepreneurship,” *Journal of Financial Economics*, Vol. 82 (3), pp. 591–629.

Konings, J., and H. Vandenbussche (2005), “Antidumping protection and markups of domestic firms”, *Journal of International Economics*, Vol. 65, No. 1, pp. 151–165.

Korinek, A., and D.X. Ng (2017), “The Macroeconomics of Superstars”, mimeo.

Koske, I., I. Wanner, R. Bitetti, and O. Barbiero (2015), “The 2013 update of the OECD's database on product market regulation: Policy insights for OECD and non-OECD countries”, OECD Economics Department Working Papers, No. 1200.

Lashkari D., A. Bauer, and J. Boussard (2019), “Information Technology and Returns to Scale”, Boston College Working Papers in Economics, No. 984.

Martin, J., and F. Mayneris (2015), "High-end variety exporters defying gravity: Micro facts and aggregate implications", *Journal of International Economics*, Vol. 96, No. 1, pp. 55–71.

Meinen, P. (2016), "Markup responses to Chinese imports", *Economics Letters*, Vol.141, pp.122–124.

Schmoch, U. (2008), "Concept of a Technology Classification for Country Comparisons, Final Report to the World Intellectual Property Organisation (WIPO)", revised in January 2013.

Squicciarini, M., and H. Dernis (2013), "A Cross-Country Characterisation of the Patenting Behaviour of Firms based on Matched Firm and Patent Data", OECD Science, Technology and Industry Working Papers, No. 2013/05.

Squicciarini, M., H. Dernis and C. Criscuolo (2013), "Measuring Patent Quality: Indicators of Technological and Economic Value", OECD Science, Technology and Industry Working Papers, No. 2013/03.

Tambe, P., Hitt, L. M., and Brynjolfsson, E. (2012), "The extroverted firm: How external information practices affect innovation and productivity", *Management Science*, Vol. 58, No. 5, pp. 843–859.

Traina, J. (2018), "Is Aggregate Market Power Increasing? Production Trends using Financial Statements", Stigler Center for the Study of the Economy and the State, New Working Paper series, No. 17.

Tybout, J. (2003), "Plant- and Firm- level evidence on 'New' Trade Theories", in*: Handbook of International Trade*, Vol.1, pp. 388–415.

Van Reenen, J. (2018), "Increasing Differences Between Firms: Market Power and the Macro-Economy,", CEP Discussion Papers dp1576, Centre for Economic Performance, LSE.

Table 1. Summary statistics in 2005 USD PPP, by digital intensity

Variable	*2001-2003, less digital intensive*				*2001-2003, digital intensive*			
	Mean	**Median**	**SD**	**N. Obs.**	**Mean**	**Median**	**SD**	**N. Obs.**
Real Gross Output ('000)	32,200	9,050	250,000	144,169	52,000	12,400	405,000	234,190
Real Value Added ('000)	9,200	2,651	98,800	144,169	13,300	2,891	147,000	234,190
Real Intermediates ('000)	15,800	3,862	125,000	144,169	29,000	6,106	212,000	234,190
Number of employees	134	47	1,475	144,169	189	48	1,366	234,190
Real Capital Stock ('000)	13,500	2,252	166,000	144,169	17,300	1,466	470,000	234,190
Log(Mark-up): Cobb-Douglas	0.20	0.14	0.21	99,153	0.32	0.16	0.40	131,128
Log(Mark-up): Translog	0.10	0.06	0.14	124,694	0.18	0.07	0.26	172,126
Variable	**2013-2014, less digital intensive**				**2013-2014, digital intensive**			
	Mean	**Median**	**SD**	**N. Obs.**	**Mean**	**Median**	**SD**	**N. Obs.**
Real Gross Output ('000)	44,600	8,340	537,000	131,069	69,700	14,300	531,000	217,299
Real Value Added ('000)	11,800	2,520	202,000	131,069	17,900	3,552	169,000	217,299
Real Intermediates ('000)	22,600	4,088	225,000	131,069	37,700	7,059	263,000	217,299
Number of employees	151	50	1,464	131,069	217	56	1,449	217,299
Real Capital Stock ('000)	26,700	2,451	567,000	131,069	31,000	1,774	485,000	217,299
Log(Mark-up): Cobb-Douglas	0.25	0.17	0.28	88,672	0.41	0.23	0.48	118,830
Log(Mark-up): Translog	0.12	0.07	0.17	108,421	0.23	0.09	0.31	156,149

Source: Author's estimations on Orbis® data. (*** p<0.01, ** p<0.05, * p<0.1).

Table 2. Different components of the digital intensity

Source: Author's estimations on Orbis® data. (*** p<0.01, ** p<0.05, * p<0.1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ICT skills (t-1)	0.015							0.003	0.003		
	(0.013)							(0.013)	(0.013)		
Software investment (t-1)		0.014***					c	0.014***	0.014***	0.013***	0.012***
		(0.003)						(0.003)	(0.003)	(0.003)	(0.003)
Interm. ICT services (t-1)			-0.002					-0.003	-0.003		
			(0.002)					(0.002)	(0.002)		
Online market access (t-1)				-0.002***				-0.002**	-0.002**	-0.002***	-0.002**
				(0.001)				(0.001)	(0.001)	(0.001)	(0.001)
Hardware (t-1)					0.001			0.001	0.001		
					(0.001)			(0.001)	(0.001)		
Interm. ICT goods (t-1)						0.003*		0.001	0.001		
						(0.002)		(0.001)	(0.001)		
ICT patent stock (t-1)							0.001**		0.001**	0.001**	0.001**
							(0.000)		(0.000)	(0.000)	(0.000)
Fixed cost (t-1)											0.042***
											(0.015)
Observations	1,021,377	1,021,377	1,021,377	1,021,377	1,021,377	910,407	1,021,377	910,407	910,407	1,021,377	1,021,377
Controls	age, K intensity	age, K intensity	age, K intensity	age, K intensity	age, K intensity	age, K intensity	age, K intensity	age, K intensity	age, K intensity	age, K intensity	age, K intensity
Fixed effects	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year
Cluster	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country

Note: Firm fixed-effect estimation where the dependent variable is firms' log-mark-ups, calculated assuming a Cobb-Douglas production function. Country-year and sector-year fixed effects included. "ICT skill" is the proportion of an industry's workforce employed in ICT-specialist occupations. "Software investment" is the ratio of industry's volume of investment in software to the industry's volume of total non-residential investment. "Intermediate ICT services" ("Intermediate ICT goods") is the ratio between an industry's intermediate consumption of services (goods) from the ICT service (goods) producing industry over the industry's output. "Online market access" is the proportion of an industry's sales carried out online. "Hardware" is the industry's volume of hardware investment over the industry's volume of total non-residential investment. "ICT patent stock" is the depreciated stock of ICT-related patents filed by the firm, over the firm's real sales, where ICT-related patents are identified using International Patent Classification (IPC) codes, following the classification presented in Schmoch (2008, revised in 2013). "Fixed cost" calculated at firm level as in De Ridder (2019) and then averaged within each country-industry excluding the one to which the firm belongs. All regressors are lagged once and standardised. Errors are clustered at the industry-country level. *** p<0.01, ** p<0.05, * p<0.1.
Source: Author's estimations on Orbis® and Patstat data, OECD Annual National Accounts, STAN, ICIO, and PIAAC; Eurostat Digital Economy and Society Statistics; National Labour Force Surveys; INTAN-Invest.

Table 3. Mark-ups and intangible assets, frontier vs non-frontier firms

	(1)	(2)	(3)	(4)
	Frontier>= 75th percentile		Frontier>= 90th percentile	
Software investment (t-1)	0.010***	0.011***	0.012***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)
Online market access (t-1)	-0.001	-0.001**	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
ICT patent stock (t-1)	0.001**	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Fixed cost, (t-1)		0.034**		0.039***
		(0.015)		(0.015)
Frontier	0.063***	0.062***	0.077***	0.073***
	(0.004)	(0.003)	(0.004)	(0.004)
Frontier#Software investment (t-1)	0.025***	0.010***	0.024***	0.011***
	(0.003)	(0.003)	(0.003)	(0.004)
Frontier#Online market access (t-1)	-0.009***	-0.002	-0.010***	-0.002
	(0.002)	(0.001)	(0.002)	(0.002)
Frontier#ICT patent stock (t-1)	-0.000	-0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Frontier#Fixed cost (t-1)		0.051***		0.051***
		(0.006)		(0.009)
Observations	1,016,770	1,016,770	1,016,770	1,016,770
Controls	age, capital intensity	age, capital intensity	age, capital intensity	age, capital intensity
Fixed effects	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year
Cluster	industry-country	industry-country	industry-country	industry-country

Note: See footnote to Table 2. "Frontier" is a dummy variable which takes value 1 if the firm belongs to the top quartile (respectively, top 10%) of the MFP distribution of the same country, industry and year, 0 otherwise for columns 1-2 vs 3-4 respectively.
Source: Author's estimations on Orbis® and Patstat data, OECD Annual National Accounts, STAN, ICIO, and PIAAC; Eurostat Digital Economy and Society Statistics; National Labour Force Surveys; INTAN-Invest.

Table 4. Mark-ups and international competition

	(1)	(2)	(3)	(4)	(5)	(6)
Software investment (t-1)		0.013***	0.013***		0.012***	0.011***
		(0.003)	(0.003)		(0.003)	(0.003)
Online market access (t-1)		-0.002***	-0.002**		-0.002**	-0.001**
		(0.001)	(0.001)		(0.001)	(0.001)
ICT patent stock (t-1)		0.001**	0.001**		0.001**	0.001**
		(0.000)	(0.000)		(0.000)	(0.000)
Openness (t-1)	-0.001	-0.002		-0.002*	-0.003**	
	(0.002)	(0.001)		(0.001)	(0.001)	
Fixed cost (t-1)				0.046***	0.042***	0.043***
				(0.015)	(0.015)	(0.015)
Import Intensity (finals from world) (t-1)			-0.001***			-0.002***
			(0.000)			(0.001)
Import Intensity (interm. JJ from world) (t-1)			0.003*			0.002
			(0.002)			(0.002)
Import Intensity (finals from China) (t-1)			0.002			0.001
			(0.001)			(0.001)
Import Intensity (interm. JJ from China) (t-1)			-0.003**			-0.003**
			(0.001)			(0.001)
Exports Intens (total to WOR) (t-1)			-0.002			-0.003
			(0.002)			(0.002)
Observations	1,021,377	1,021,377	1,014,591	1,021,377	1,021,377	1,014,591
Controls	age, capital intensity	age, capital intensity	age, capital intensity	age, capital intensity	age, capital intensity	age, capital intensity
Fixed effects	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year
Cluster	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country

Note: See footnote to Table 2. "Openness intensity" is the sum of total imports and exports over the industry output. "Import Intensity (finals from the world)" and "Import Intensity (interm. *JJ* from world)" identify, respectively, imports of final and intermediate goods from any foreign country but China. Imports of intermediates only include intermediates produced in the same industry. The same concepts apply for imports from China, in the variables so identified. Intensities are calculated as country-industry trade flows over output.
Source: Author's estimations on Orbis® and Patstat data, OECD Annual National Accounts, STAN, ICIO, and PIAAC; Eurostat Digital Economy and Society Statistics; National Labour Force Surveys; INTAN-Invest.

Table 5. Mark-ups and product market regulation

	(1)	(2)	(3)	(4)	(5)
Software investment (t-1)		0.014***	0.013***	0.013***	0.012***
		(0.003)	(0.003)	(0.004)	(0.004)
Online market access (t-1)		-0.002***	-0.002***	-0.001**	-0.001**
		(0.001)	(0.001)	(0.001)	(0.001)
ICT patent stock (t-1)		0.001**	0.001**	0.001**	0.001**
		(0.000)	(0.000)	(0.000)	(0.000)
Fixed cost (t-1)			0.045***		0.033***
			(0.015)		(0.012)
Upstream PMR (t-1)	-0.013**	-0.016**	-0.019***	-0.058***	-0.054***
	(0.007)	(0.006)	(0.006)	(0.020)	(0.020)
Regulated#Software investment (t-1)				-0.009	-0.007
				(0.006)	(0.006)
Regulated#Online market access (t-1)				-0.004**	-0.002
				(0.002)	(0.002)
Regulated#ICT patent stock (t-1)				0.000	0.000
				(0.001)	(0.001)
Regulated#Fixed cost (t-1)					-0.007
					(0.018)
Regulated#Upstream PMR (t-1)				0.044**	0.036**
				(0.020)	(0.018)
Observations	1,021,377	1,021,377	1,021,377	1,021,377	1,021,377
Controls	age, capital intensity	age, capital intensity	age, capital intensity	age, capital intensity	age, capital intensity
Fixed effects	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year
Cluster	industry-country	industry-country	industry-country	industry-country	industry-country

Note: See footnote to Table 2 “Upstream PMR” measures the extent to which the output of the regulated industries is used as intermediate input in other industries. “Regulated” takes value 1 for firms belonging to regulated industries (electricity, gas, telecom, post and air, rail and road transports, and retail and professional services).
Source: Author’s estimations on Orbis® and Patstat data, OECD Annual National Accounts, STAN, ICIO, and PIAAC; Eurostat Digital Economy and Society Statistics; National Labour Force Surveys; INTAN-Invest.

Table 6. Mark-ups and concentration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Software investment (t-1)	0.016***			0.016***	0.016***			0.016***	0.016***
	(0.005)			(0.005)	(0.005)			(0.005)	(0.005)
Online market access (t-1)	-0.002*			-0.002*	-0.002*			-0.002*	-0.002*
	(0.001)			(0.001)	(0.001)			(0.001)	(0.001)
ICT patent stock (t-1)	0.001**			0.001**	0.001**			0.001**	0.001**
	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Fixed cost (t-1)	0.017***			0.017***	0.016**			0.017***	0.016**
	(0.007)			(0.007)	(0.007)			(0.007)	(0.007)
C4 (country-industry)		0.000	0.013**	0.000	0.012**				
		(0.003)	(0.005)	(0.003)	(0.005)				
Squared C4 (country-industry)			-0.011***		-0.010***				
			(0.004)		(0.004)				
C8 (country-industry)						-0.000	0.015**	-0.000	0.013**
						(0.003)	(0.006)	(0.003)	(0.006)
Squared C8 (country-industry)							-0.014***		-0.012***
							(0.005)		(0.005)
Observations	676,204	676,204	676,204	676,204	676,204	676,204	676,204	676,204	676,204
Controls	age, capital intensity	age, capital intensity	age, capital intensity	age, capital intensity	age, capital intensity	age, capital intensity	age, capital intensity	age, capital intensity	age, capital intensity
Fixed effects	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year
Cluster	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country

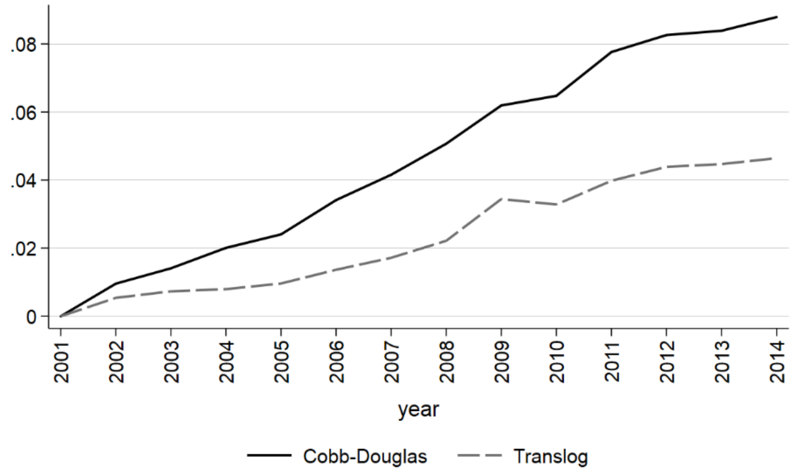
Note: See footnote to Table 2. C4 (resp. C8) is the share of output produced by the largest 4 (resp. 8) business groups over the industry's total output.
Source: Author's estimations on Orbis® and Patstat data, OECD Annual National Accounts, STAN, ICIO, and PIAAC; Eurostat Digital Economy and Society Statistics; National Labour Force Surveys; INTAN-Invest.

Table 7. Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline	Alternative definition of ICT patents (Inaba and Squicciarini, 2017)	All alternative explanations	Firm MFP control	Firm size control (employment)	R&D expenditure intensity control	Country-industry-year dummies	Translog-based mark-ups
Software investment (t-1)	0.012***	0.012***	0.012***	0.008**	0.010***	0.007***		0.007***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)		(0.002)
Online market access (t-1)	-0.002**	-0.002**	-0.002**	-0.001*	-0.001**	-0.001***		-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		(0.000)
ICT patent stock (t-1)	0.001**	0.001*	0.001**	0.001**	0.001***	0.001**	0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,021,377	1,021,377	1,021,377	1,016,770	1,021,377	1,019,687	1,021,266	1,369,856
Controls	age, capital intensity, fixed cost	age, capital intensity, fixed cost	age, capital intensity, fixed cost, openness, upstream PMR	age, capital intensity, fixed cost, firm MFP	age, capital intensity, fixed cost, firm size	age, capital intensity, fixed cost, R&D intensity	age, capital intensity	age, capital intensity, fixed cost
Fixed effects	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-year, sector-year	firm, country-industry-year	firm, country-year, sector-year
Cluster	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country

Note: See footnote to Table 2. "ICT patent stock" is the firm's depreciated stock of ICT-related patents over the firm's real sales - different definitions apply for this table.
Source: Author's estimations on Orbis® and Patstat data, OECD Annual National Accounts, STAN, ICIO, and PIAAC; Eurostat Digital Economy and Society Statistics; National Labour Force Surveys; INTAN-Invest.

Figure 1. Average of firm log mark-up: growth 2001-2014

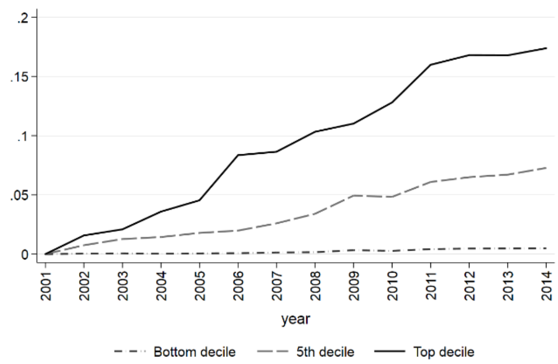


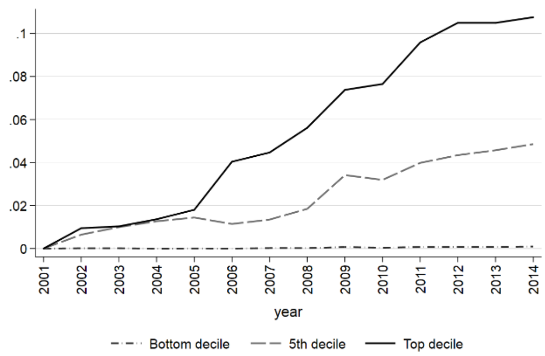
Note: Unconditional averages of firm log mark-ups, for all firms in the manufacturing and non-financial market service sectors included in the sample. The figure plots log mark-ups and indexes the 2001 level to 0, hence the vertical axes represent log-differences from the starting year which, given the magnitudes, approximates well for growth rates.
Source: Author's estimations on Orbis® data.

Figure 2. Log Mark-up growth over time (2001-2014) in different parts of the distribution

(a) Cobb-Douglas

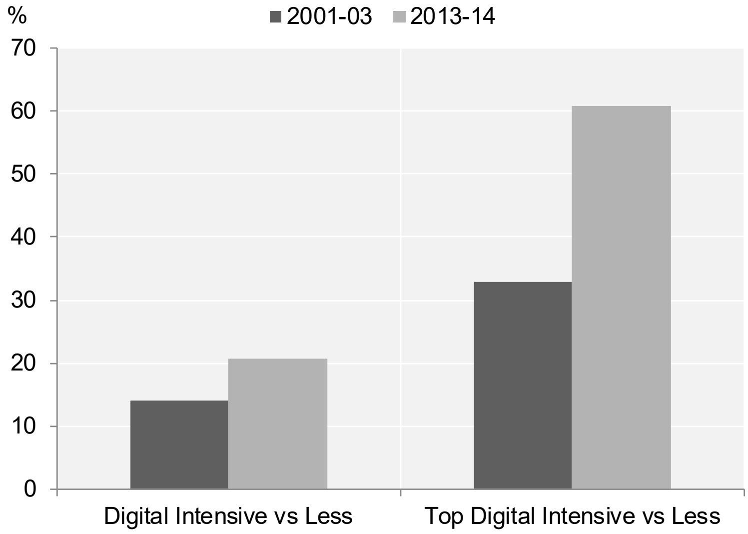
(b)Translog





Note: Unconditional averages of firm log mark-ups in the chosen part of the distribution of mark-ups. Deciles of the distribution are defined relative to the rest of the firms in each 2-digit industry-year. All firms in the manufacturing and non-financial market service sectors included in the sample. The figures plots log mark-ups and indexes the 2001 level to 0, hence the vertical axes represent log-differences from the starting year. Panel (a) is based on a Cobb-Douglas production function, whereas panel (b) on a Translog production function.
Source: Author's estimations on Orbis® data.

Figure 3. Average percentage differences in mark-ups between firms in less digital intensive and in digital intensive industries at the beginning and at the end of the sample period



Note: The graphs report the estimates of a pooled OLS regression explaining firm log mark-ups in the period, keeping into account firm's capital intensity, age, and country-year of operation, as well as a dummy variable with value 1 if the industry of operation is digital intensive vs less intensive (specifications on the left in the graph), or if the industry of operation is among the top 25% of digital intensive industries vs. not (specifications on the right in the graph). Estimates of mark-ups assuming a Cobb Douglas production function. Standard errors are clustered at the firm level. All coefficients are significant at the 1% confidence level.
Source: Author's estimations on Orbis® data.

Appendix

Annex A. Deriving an expression for mark-ups

Consider and economy with N firms, indexed by $i=1,...,N$. Firms are heterogeneous in their productivity. In each period t, firm minimises the contemporaneous cost of production given the production function that transforms inputs into the output produced by the technology $Q_{it}(\cdot)$:

$$Q_{it} = Q(\mathrm{X}_{it}^{1},...,\mathrm{X}_{it}^{V},\mathrm{K}_{it},\Omega_{it}) \tag{7}$$

The firm relies on V variable inputs, such as labour and intermediate inputs, and on a capital stock, K_{it}. Ω_{it} is a firm-specific productivity term. Following De Loecker and Warzynski (2012), consider the associated Lagrangian objective function:

$$L(\mathrm{X}_{it}^{1},...,\mathrm{X}_{it}^{V},\mathrm{K}_{it},\Omega_{it}) = \sum_{v=1}^{V} p_{it}^{X^V} X_{it}^{V} + r_{it}K_{it} - \lambda_{it}(\mathrm{Q}_{it} - \mathrm{Q}_{it}(\cdot)), \tag{8}$$

where $p_{it}^{X^V}$ and r_{it} denote a firm's input price for a variable input v and for capital, respectively. The first order condition for any variable input free of adjustment cost is given by:

$$\frac{\partial L_{it}}{\partial X_{it}^{V}} = P_{it}^{X^V} - \lambda_{it}\frac{\partial Q_{it}(\cdot)}{\partial X_{it}^{V}} = 0. \tag{9}$$

Rearranging terms and multiplying both sides by $\frac{X_{it}^{v}}{Q_{it}}$, we get:

$$\frac{\partial Q_{it}(\cdot)}{\partial X_{it}^{V}}\frac{X_{it}^{V}}{Q_{it}} = \frac{1}{\lambda_{it}}\frac{P_{it}^{X^V} X_{it}^{V}}{Q_{it}}. \tag{10}$$

Therefore, the cost minimisation implies that the optimal input demand is satisfied when a firm equalises the output elasticity of any variable input X_{it}^{V} (left hand side of the previous formula) to $\frac{1}{\lambda_{it}}\frac{P_{it}^{X^V} X_{it}^{V}}{Q_{it}}$.

The Lagrange multiplier λ is the value of the objective function as we relax the output constraint. Hence, it is a direct measure of marginal cost. We define mark-ups as $\mu_{it} = \frac{P_{it}}{\lambda_{it}}$, i.e., the price-marginal cost fraction. Note that P_{it} is the price of the output good. Using this definition, equation (10) can be rewritten as:

$$\mu_{it} = \theta_{it}^{X} \frac{P_{it} Q_{it}}{P_{it}^{X^V} X_{it}^{V}}, \tag{11}$$

where $\theta_{it}^{X} = \frac{\partial Q_{it}(\cdot)}{\partial X_{it}^{V}} \frac{X_{it}^{V}}{Q_{it}}$ is the output elasticity of the variable input *X*, and $\frac{P_{it} Q_{it}}{P_{it}^{X^V} X_{it}^{V}}$ is the inverse of the revenue share of the variable input. Therefore, mark-ups are given by the ratio between the output elasticity of the variable input chosen and its revenue share. Note that the expression is derived without specifying any demand system, and do not restrict the output elasticity. However, the output elasticity will depend on the specific production function adopted.

Annex B. Data: additional details

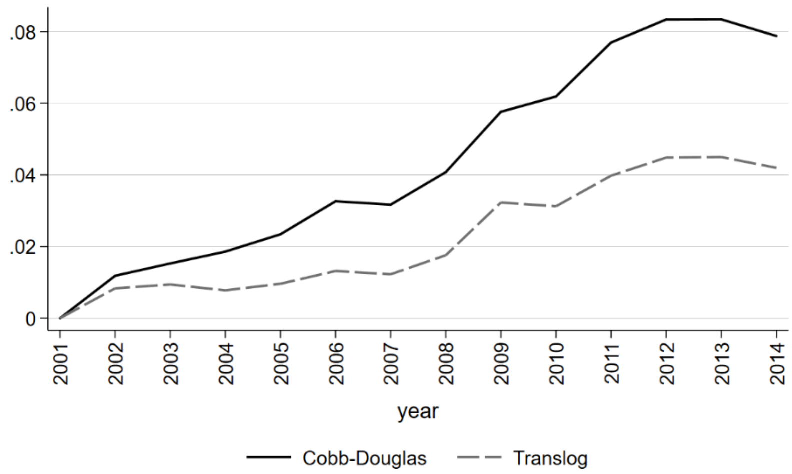
Table A.1. Taxonomy of industries by quartile of digital intensity, 2013-15

Industry denomination	Quartile of digital intensity: 2001-03	Quartile of digital intensity: 2013-15
Food products, beverages and tobacco	Low	Low
Textiles, wearing apparel, leather	Medium-low	Medium-low
Wood and paper products, and printing	Medium-high	Medium-high
Chemicals and chemical products	Medium-low	Medium-low
Pharmaceutical products	Medium-low	Medium-low
Rubber and plastics products	Medium-low	Medium-low
Basic metals and fabricated metal products	Medium-low	Medium-low
Computer, electronic and optical products	High	Medium-high
Electrical equipment	Medium-high	Medium-high
Machinery and equipment n.e.c.	High	Medium-high
Transport equipment	High	High
Furniture; other manufacturing; repairs of computers	Medium-high	Medium-high
Wholesale and retail trade, repair	Medium-high	Medium-high
Transportation and storage	Low	Low
Accommodation and food service activities	Low	Low
Publishing, audiovisual and broadcasting	Medium-high	Medium-high
Telecommunications	High	High
IT and other information services	High	High
Legal and accounting activities, etc.	High	High
Scientific research and development	Medium-high	High
Advertising and market research; other business services	High	High
Administrative and support service activities	High	High

Note: All indicators are expressed as industry intensities. The industry values are averages across countries and years. The taxonomy is based on information for the following countries: Australia, Austria, Denmark, Finland, France, Italy, Japan, the Netherlands, Norway, Sweden, the United Kingdom, the United States, for which values for all indicators in all considered industries and years are non-missing, with the exception of robot use and online sales, where some industries are not sampled.
Source: Calvino et al. (2018), based on OECD Annual National Accounts, STAN, ICIO, and PIAAC; International Federation of Robotics; World Bank; Eurostat Digital Economy and Society Statistics; National Labour Force Surveys; INTAN-Invest; and other national sources.

Annex C. Evolution of mark-ups, additional graphs

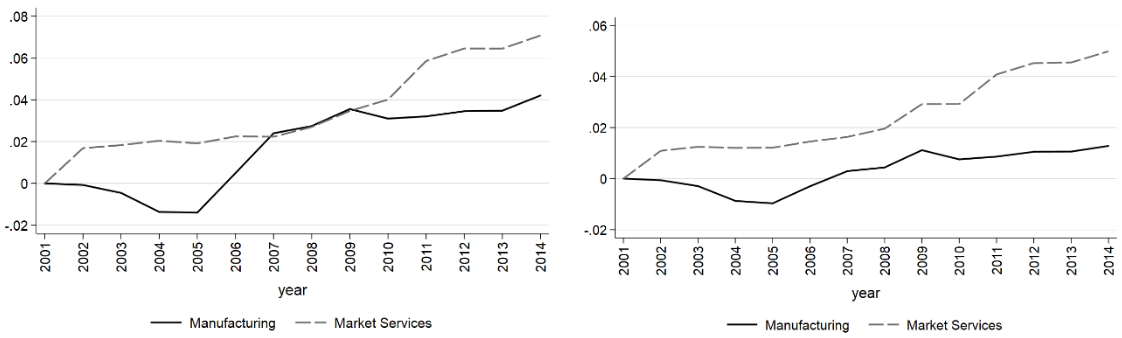
Figure A 1. Within-country average of firm log mark-up: growth 2001-2014



Note: The figure reports the estimated year dummies of a panel-data regression of average log mark-ups within countries (i.e., including country fixed effects). The estimates for the baseline year 2001 are normalised to 0. The values correspond to the within-country average since 2001. All coefficients are significant at the 1% confidence level.
Source: Author's estimations on Orbis® data.

Figure A 2. Log Mark-up growth over time (2001-2014), manufacturing vs. services

(a) Cobb-Douglas (b) Trsnslog



Note: Unconditional averages of firm log mark-ups, for manufacturing and non-financial market service sectors separately. The figure plots log mark-ups and indexes the 2001 level to 0, hence the vertical axes represent log-differences from the starting year which, given the magnitudes, approximates well for growth rates. Panel (a) is based on a Cobb-Douglas production function, whereas panel (b) on a Translog production function.
Source: Author's estimations on Orbis® data.

Annex D. Mark-ups and digital intensity

Table A.2 Mark-ups and digital intensity, baseline regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2001-2003				2013-14			
Digital intensive	0.132***	0.118***			0.188***	0.151***		
	(0.002)	(0.002)			(0.002)	(0.002)		
Top-digital Intensive			0.285***	0.269***			0.475***	0.439***
			(0.003)	(0.002)			(0.003)	(0.003)
Observations	230,281	230,281	230,281	230,281	207,502	207,502	207,502	207,502
R-squared	0.059	0.090	0.176	0.193	0.090	0.147	0.309	0.328
Controls	age, K intensity	age, K intensity, MFP	age, K intensity	age, K intensity, MFP	age, K intensity	age, K intensity, MFP	age, K intensity	age, K intensity, MFP
Fixed Effects	country-year	country-year	country-year	country-year	country-year	country-year	country-year	country-year
Cluster	id	id	id	id	id	id	id	id

Note: Results of estimating OLS regressions where the dependent variable is firm's log-mark-ups, calculated assuming a Cobb-Douglas production function. "Digital intensive" is a dummy variable with value 1 if the industry is above the median of all 36 considered industry by digital intensity, as ranked in Calvino et al. (2018). "Top digital intensive" is a dummy variable with value 1 if the industry is in the top quartile of digital intensity instead. All controls refer to *t-1*. Errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.
Source: Author's estimations on Orbis® data

Table A.3. Mark-ups and digital intensity, mark-ups calculated assuming a Translog production function

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2001-2003				2013-14			
Digital intensive	0.084***	0.076***			0.122***	0.101***		
	(0.001)	(0.001)			(0.001)	(0.001)		
Top-digital Intensive			0.221***	0.213***			0.350***	0.350***
			(0.002)	(0.002)			(0.002)	(0.022)
Observations	296,820	296,820	296,820	296,820	264,570	264,570	264,570	264,570
R-squared	0.060	0.085	0.227	0.240	0.098	0.149	0.362	0.362
Controls	age, K intensity	age, K intensity, MFP	age, K intensity	age, K intensity, MFP	age, K intensity	age, K intensity, MFP	age, K intensity	age, K intensity, MFP
Fixed Effects	country-year	country-year	country-year	country-year	country-year	country-year	country-year	country-year
Cluster	id	id	id	id	id	id	id	id

Note: Results of estimating OLS regressions where the dependent variable is firms' log-mark-ups, calculated assuming a Translog production function. See also footnote to Table A.2 *** p<0.01, ** p<0.05, * p<0.1.
Source: Author's estimations on Orbis® data.

Table A.4. Mark-ups and digital intensity, errors clustered at the industry-country level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2001-2003				2013-14			
Digital intensive	0.132***	0.118***			0.188***	0.151***		
	(0.027)	(0.025)			(0.026)	(0.024)		
Top-digital Intensive			0.285***	0.269***			0.475***	0.439***
			(0.036)	(0.034)			(0.032)	(0.032)
Observations	230,281	230,281	230,281	230,281	207,502	207,502	207,502	207,502
R-squared	0.059	0.090	0.176	0.193	0.090	0.147	0.309	0.328
Controls	age, K intensity	age, K intensity, MFP	age, K intensity	age, K intensity, MFP	age, K intensity	age, K intensity, MFP	age, K intensity	age, K intensity, MFP
Fixed Effects	country-year	country-year	country-year	country-year	country-year	country-year	country-year	country-year
Cluster	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country	industry-country

Note: Results of estimating OLS regressions where the dependent variable is firms' log-mark-ups, calculated assuming a Cobb-Douglas production function. See also footnote to Table A.2. Errors are clustered at the industry-country level. *** p<0.01, ** p<0.05, * p<0.1.

Source: Author's estimations on Orbis® data.

Table A.5. Mark-ups and digital intensity, whole period (2001-2014)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cobb-Douglas (2001-2014)				Translog (2001-2014)			
Digital intensive	0.167***	0.134***			0.108***	0.106***		
	(0.002)	(0.001)			(0.001)	(0.001)		
Top-digital Intensive			0.349***	0.317***			0.254***	0.254***
			(0.002)	(0.002)			(0.001)	(0.001)
Observations	1,124,920	1,124,920	1,124,920	1,124,920	1,456,356	1,456,356	1,456,356	1,456,356
R-squared	0.087	0.134	0.217	0.241	0.096	0.097	0.263	0.263
Controls	age, K intensity	age, K intensity, MFP	age, K intensity	age, K intensity, MFP	age, K intensity	age, K intensity, MFP	age, K intensity	age, K intensity, MFP
Fixed Effects	country-year	country-year	country-year	country-year	country-year	country-year	country-year	country-year
Cluster	id	id	id	id	id	id	id	id

Note: Results of estimating OLS regressions where the dependent variable is firms' log-mark-ups, calculated assuming a Cobb-Douglas production function in the first 4 columns, and a Translog production function in the last 4. "Digital intensive" is a dummy variable with value 1 if in the period 2001-2003 the industry is above the median of all 36 considered industry by digital intensity, as ranked in Calvino et al. (2018). "Top digital intensive" is a dummy variable with value 1 if in the period 2001-2003 the industry is in the top quartile of digital intensity instead. All controls refer to t-1. Errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Source: Author's estimations on Orbis® data.

Table A.6. Mark-ups and digital intensity, manufacturing vs. services

	(1)	(2)	(3)	(4)
	2001-2003		2013-2014	
Service Digital-Intensive	0.342***	0.325***	0.370***	0.329***
	(0.003)	(0.003)	(0.003)	(0.003)
Service Less-Digital Intensive	0.155***	0.154***	0.123***	0.121***
	(0.002)	(0.002)	(0.002)	(0.002)
Manufacturing Digital-Intensive	-0.011***	-0.013***	-0.035***	-0.036***
	(0.001)	(0.001)	(0.002)	(0.002)
Observations	230,281	230,281	207,502	207,502
R-squared	0.221	0.236	0.211	0.243
Controls	age, K intensity	age, K intensity, MFP	age, K intensity	age, K intensity, MFP
Fixed Effects	country-year	country-year	country-year	country-year
Cluster	id	id	id	id

Note: Results of estimating OLS regressions where the dependent variable is firms' log-mark-ups, calculated assuming a Cobb-Douglas production function. "Services Digital" is a dummy variable with value 1 if the firm operates in a services industry categorised as digital intensive; "Service Less-Digital" if the firm operates in a less digital intensive service industry, "Manufacturing Digital" if the firm operates in a digital intensive manufacturing industry. The base category is "Manufacturing Less-Digital", if the firm operates in a less digital intensive manufacturing industry. Errors are clustered at the industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Source: Author's estimations on Orbis® data.

Annex E. Intangibles, digital technologies and mark-ups: additional results

Table A.7. Summary statistics in 2005 USD PPP, main explanatory variables of interest for a balanced sample of non-missing regressors

	Mean	*Median*	*SD*	*N. of obs.*
Log(Mark-up): Cobb-Douglas	0.30	0.17	0.38	1,021,377
Real Gross Output ('000)	27,689	7,667	71,546	1,021,377
Real Value Added ('000)	15,356	3,072	157,803	1,021,377
Real Intermediates ('000)	22,972	4,287	245,594	1,021,377
Real Capital Stock ('000)	12,073	1,803	35,762	1,021,377
Number of employees	148	55	283	1,021,377
ICT patent stock intensity	0.09	0.00	3.72	1,021,377
ICT patent stock intensity (alternative definition)	0.07	0.00	3.12	1,021,377
ICT patent stock intensity (citation weighted)	0.00	0.00	0.19	1,021,377
Fixed cost (firm level)	11.40	5.33	22.18	1,021,377
Fixed cost, other countries industry mean	13.18	8.33	13.05	1,021,377
Fixed cost, industry mean	14.38	9.19	15.20	1,021,377
Fixed cost, mean of top quartile	28.15	22.47	21.32	1,021,377
Human capital intensity	3.91	1.50	10.45	1,021,377
Software investment intensity	14.39	8.35	15.24	1,021,377
ICT tangible investment intensity	7.11	4.59	6.37	1,021,377
Online market access intensity	8.65	6.78	7.70	1,021,377
Intermediate ICT goods intensity	0.48	0.24	0.70	1,021,377
Interm. ICT services intensity	1.26	0.65	2.06	910,407
Openness intensity	31.23	23.00	27.17	1,021,377
Upstream PMR	16.40	11.47	11.96	1,021,377
Concentration (C4)	21.54	15.47	19.63	676,204
Concentration (C8)	28.30	21.35	23.40	676,204

Note: The statistics are computed on the sample used for the most complete regression (ref. Table 9).
Source: Author's estimations on Orbis® and Patstat data, OECD Annual National Accounts, STAN, ICIO, and PIAAC; Eurostat Digital Economy and Society Statistics; National Labour Force Surveys; INTAN-Invest.

Table A.8. Mark-ups and intangible assets, manufacturing vs. services

	(1)	(2)	(3)
	Baseline	Dummy: services=1	Dummy: services=1
Software investment (t-1)	0.012***	0.006	0.006
	(0.003)	(0.004)	(0.004)
Online market access (t-1)	-0.002**	-0.002***	-0.002**
	(0.001)	(0.001)	(0.001)
ICT patent stock (t-1)	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)
Fixed cost (t-1)	0.042***		0.083***
	(0.015)		(0.013)
Dummy#Software investment (t-1)		0.013**	0.011**
		(0.005)	(0.005)
Dummy#Online market access (t-1)		0.003	0.003*
		(0.002)	(0.002)
Dummy#ICT patent stock (t-1)		-0.000	0.000
		(0.001)	(0.001)
Service dummy#Fixed cost (t-1)			-0.042**
			(0.020)
Observations	1,021,377	1,021,377	1,021,377
Reference group	n.a.	manuf	manuf
Controls	age, capital intensity	age, capital intensity	age, capital intensity
Fixed effects	firm, country-year, sector-year	firm, country-year	firm, country-year
Cluster	industry-country	industry-country	industry-country

Note: Firm fixed-effect estimation of firms' log-mark-ups, calculated assuming a Cobb-Douglas production function. Country-year fixed effects included. Column 1 is the baseline specification and corresponds to column 11 in Table 2, so it also controls for sector-year fixed effects (manufacturing vs services). "Dummy" is a dummy variable which takes value 1 for the group that is specified in the column's header, and 0 for the reference group specified at the bottom of the table. All other regressors are as in Table 2 and all lagged once and standardised. Errors are clustered at the industry-country level. *** p<0.01, ** p<0.05, * p<0.1.
Source: Author's estimations on Orbis® and Patstat data, OECD Annual National Accounts, STAN, ICIO, and PIAAC; Eurostat Digital Economy and Society Statistics; National Labour Force Surveys; INTAN-Invest.

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