

Please cite this paper as:

Calligaris, S., C. Criscuolo and L. Marcolin (2018), "Mark-ups in the digital era", *OECD Science, Technology and Industry Working Papers*, 2018/10, OECD Publishing, Paris.
<http://dx.doi.org/10.1787/4efe2d25-en>



OECD Science, Technology and Industry
Working Papers 2018/10

Mark-ups in the digital era

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JEL Classification: D2, L1, L2, O33

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The release of this working paper has been authorised by Andrew Wyckoff, OECD Director for Science, Technology and Innovation and by Luiz de Mello, OECD Director and Special Advisor to the Chief Economist. The analysis proposed in this paper was declassified following the November 2017 meeting of the OECD Committee on Industry, Innovation and Entrepreneurship.

This publication is a contribution to the OECD Going Digital project, which aims to provide policymakers with the tools they need to help their economies and societies prosper in an increasingly digital and data-driven world. For more information, visit www.oecd.org/going-digital/#GoingDigital

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MARK-UPS IN THE DIGITAL ERA

Sara Calligaris, Chiara Criscuolo, Luca Marcolin¹

ABSTRACT

This article examines the evolution of firm mark-ups across 26 countries for the period 2001-14. It also discusses and investigates empirically how this can be related to the degree of digital transformation in sectors. Four main facts emerge: i) mark-ups are increasing over the period, on average across country; ii) this result is driven by firms at the top of the mark-up distribution, while the bottom half of the distribution exhibits a flat trend over time; (iii) mark-ups are higher in digital-intensive sectors than in less-digitally intensive sectors; (iv) mark-up differentials between digitally-intensive and less-digitally-intensive sectors have increased significantly over time.

Keywords: Mark-Ups; Market Power; Digitalization; Technological Change.
JEL Codes: D2; L1; L2; O33.

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1. Introduction

Digital technologies are transforming the way firms produce, upscale and compete. They allow firms to leverage ever larger networks of consumers, access multiple geographical and product markets almost instantaneously, and exploit increasing returns to scale from intangible assets. These factors should be contributing to a general increase in productivity, yet OECD analysis reveals that across much of the OECD productivity growth is lacklustre. This has led some to suggest that we are entering into another productivity paradox – where we see ICT everywhere but in the productivity statistics (van Ark, 2016).

Recent OECD work (Andrews et al., 2016) sheds light on this paradox by revealing that, against a broad context of the slowdown in productivity, frontier firms, and especially those in the ICT service sector, have had significant productivity gains relative to other firms in the market. These firms are on average larger and more capital intensive, more likely to be part of multinational corporations; comparatively file more patents and own larger stocks of patents (OECD, 2015). Non-frontier firms, and in particular SMEs, may have not been able to fully exploit the potential of digital technologies, also because they often lag behind in terms of adoption and may lack the technical personnel and required digital skills. More recently, Bessen (2017) shows evidence that the share of revenue captured by the top-firms in a sector is highly correlated with IT adoption (proprietary IT systems, proxied by share of IT workers) even after taking into account mergers and acquisitions or entrepreneurship activity.

The sustained and growing gap between the frontier firms and the rest is surprising because the benefits of digital technologies are diffused, via improved real-time measurement, cheaper business experimentation, easier sharing of ideas, global reach in terms of inputs and customers, and faster scaling-up. Generally, digital technologies are associated with lower costs of operations and of entry in a market, even across borders, thus potentially increasing competition among firms. For instance, access to online platforms such as E-bay is already enabling SMEs to engage in cross-border trade, and transform them in micro-multinational enterprises (Lendle et al., 2013), by reducing the cost of exploring new markets and of linking to an international production chain (OECD, 2016). Furthermore, market power may be hard to assert in the longer term, given the speed with which innovation takes place and market boundaries change in a digital context. Historically, the emergence of new business models involving digital technologies, such as platforms, has also increased competition in other, non-digital markets, such as in the case of Airbnb and the hotel industry or Amazon in the retail sector. This makes the persistent gap in productivity a mystery that is broadly interpreted as a “break down in the diffusion machine.”

The potential causes for this are varied and include the fact that firms at the frontier are very innovative and may benefit from combinatorial innovation; much of the know-how may be protected by intellectual property rights that provide legal protection that limits diffusion; and new digital business models rely on the intensive use of knowledge assets, which can be re-used with a marginal cost to replicate that is often close to zero, allowing digital companies to scale up faster and more easily, and generate increasing returns to scale. 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

the pervasive power of data analytics. Over time, these characteristics may help industry leaders sustain and advance their position, if they represent an additional obstacle to the entry of new players, and slow down the growth of competitors.

There are different ways of characterising the competitive environment and the dynamism of a sector and its changes over time. Recent evidence uses entry and exit rates of businesses, as well churning rates and excess job reallocation rates, to proxy for business dynamism (e.g. Blanchenay et al., 2017). The study shows that business dynamism has decreased over time, and that this decline has been stronger in IT and telecommunication manufacturing and services. Calvino and Criscuolo (forthcoming) further show that the digital transformation translates in more or less dynamism of the economy depending on which of the different dimensions of the digital transformation the analysis focuses on, such as access to e-commerce or automation.

A decline in business dynamism can also be reflected by an increase in concentration. CEA (2016) provides a recent systematic review of industry-specific and cross-industry studies focused on concentration, and highlights that the majority of U.S. industries has experienced an increase in the revenue share held by the 50 largest companies between 1997 and 2012. Autor et al. (2017), Bessen (2017), Gutierrez and Philippon (2016, 2017a,b), and Grullon et al. (2017) 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. (2017) 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 share. Bessen (2017) finds that the use of proprietary IT systems is strongly associated with industry concentration across a wide range of sectors. Gutierrez and Philippon (2017a) show that the concentration has increased in the U.S. and decreased in Europe, while Gutierrez and Philippon (2016, 2017b) establish a link between increased concentration and a decline in industries’ investment, holding other market characteristics constant.

However, measures of concentration or business dynamism based on entry and exit rates might suffer from misreporting and mismeasurement biases. This is the case when the analysis cannot rely on Census data, as pointed out by Ali et al. (2009). Measurement issues aside, industries with high concentration can be very competitive if, for instance, the threat of entry is high (Griffith and Harrison, 2006), or if the increase in concentration is not large enough to matter in the aggregate. This is the view of Shapiro’s (2017) who stresses that high concentration in certain industries at the country-wide level may not imply high concentration at the local level in many locations. Furthermore, an increase in domestic concentration may be at least partially compensated by increased imports from foreign markets (Gutierrez and Philippon, 2017b).

Other studies have used different measures of market power including firms’ profits, returns on investment or, for listed firms, dividends and market capitalisation. For example, McKinsey Global Institute (2015a) shows that variance in corporate profits has increased in time, both within industries (the best companies enjoy ever increasing growth in profits relative to their competitors) and between industries, with some industries leaving others significantly behind in profitability. Furman and Orszag (2015) and CEA (2016) also point to increased returns on invested capital as a proxy for increased profitability of firms in the United States, and show that these returns are increasingly persistent. Furman and Orszag (2015) further link the rise in profits to income inequality, Zingales (2017) to firms’ influence and political power. Barkai (2016) finds that the decrease in labour share of value added in the United States 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 sectors which experienced a higher decline the labour shares between 1997 and 2012 also displayed a higher increase in product market concentration. Similarly, Grullon et al. (2017) highlight that U.S. industries experiencing the highest increase in concentration also

increased profits the most. Eggertsson et al. (2018) use a decline in real interest rates and the mentioned rise of profits in the U.S. to explain four macro-economic phenomena, including an increase in firms' Tobin's Q. Anderson et al. (2018), instead, find that profit margins between 1979-2014 have remained approximately constant, but their analysis covers the U.S. retail sector only.

The present paper assesses the relationship between changes in competitive environment and the digital transformation focusing on a different measure of market power, i.e. changes in mark-up pricing. Mark-ups, defined as the ratio of unit price over marginal cost, are different from unity when markets are not perfectly competitive, e.g. when products are differentiated or there are barriers to entry. High mark-ups can also be related to other features of production, such as large fixed costs, a high degree of innovation or a high value of embedded intangibles may give rise to mark-up pricing (Martins et al., 1996), or international linkages (e.g. De Loecker and Warzynski, 2012).

Martins et al. (1996) analyse the impact of imperfections in product markets on the price setting of firms, and estimate mark-ups extending the methodology first proposed by Hall (1986), and later modified by Roeger (1995). They relate mark-ups with the structure of the industry and explore the evolution of mark-ups over the business cycle across 14 OECD countries for manufacturing and selected services sectors for 1980-92. They show that departures from perfect competition are very common in the manufacturing sector, but even more in service sectors. Moreover, although high mark-ups might be a sign of lack of competition, they may also be related to the market structure prevailing in an industry.

This report examines dynamics of estimated firm mark-ups across 26 countries for the period 2001-14. It estimates firm-level mark-ups as proposed in the work of De Loecker and Warzynski (2012), who build on Hall (1986). Mark-ups are then linked to measures of "digital intensity" of sectors, in order to ascertain whether differences in industries' exposure to digitalisation are related to differences in mark-ups across industries, and how this relationship has changed over time. The analysis finds that: i) average mark-ups are increasing over time; ii) this result seems to be driven by the top decile of the mark-ups distribution; iii) firms belonging to top digitalized sectors have on average higher mark-ups; iv) the difference in average firms' mark-ups between digital intensive and less digital intensive sectors is stronger now than in the past.

The increase in mark-ups (as in point (i) here above) mirrors evidence provided by De Loecker and Eeckhout (2017) for the United States. Following De Loecker and Warzynski (2012) too, they estimate mark-ups over a long time horizon for publicly-traded companies in the U.S. and report a significant increase in mark-ups since the 1980s. Traina (2018), however, argues that accounting for marketing and management expenses appropriately in the estimation of mark-ups reduces the magnitude of the increase in mark-ups over time. Lastly, the same methodology first applied to cross-country data in the present study is used in Andrews et al. (forthcoming), who confirm the existence of a positive trend in mark-ups in OECD countries, and especially in service sectors.

The paper proceeds as follows: Section 2. describes the methodology adopted to estimate mark-ups; Section 3. describes the dataset used, including the definition of digital sectors; Section 4. presents the main results; section 5. concludes.

2. Methodology

The report estimates firm-level mark-ups on the basis proposed in the work of De Loecker and Warzynski (2012), who build on Hall (1986). Both methodologies estimate mark-ups with a so-called “production function approach”, as no assumption is required on the shape of demand faced by companies and on how firms compete. The methodology requires “only” a panel of firm-level output and input data, and the assumptions that (i) at least one input of production can be adjusted without frictions, and that (ii) firms produce by minimizing their costs. Furthermore, although an explicit treatment of the production function is needed, the methodology is very flexible in that it can retrieve mark-ups when output is expressed as a function of inputs in many different ways. Lastly, while Hall (1986) and its follow-up in Roeger (1995) could only retrieve average mark-ups at the industry level given data limitations, thus restricting the analyses and policy discussions which could rely on the methodology, De Loecker and Warzynski (2012) can estimate firm-specific mark-ups.

Mark-up here 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 condition of the firm’s cost minimization problem with respect to the flexible input, and corresponds to the ratio between the elasticity of output with respect to the flexible input (i.e., the percentage increase in output when the variable input increases by 1%), OE_{it}^m , and the cost of the variable input as a share of the firm’s revenue, IS_{it}^m .

$$\mu_{it} = \frac{p_{it}}{c_{it}} = \frac{OE_{it}^m}{IS_{it}^m} \quad (1)$$

Intermediates (as opposed to labour) are assumed 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.

While IS_{it}^m is observed in the data, OE_{it}^m requires estimating a production function, i.e. the relationship between a firm’s output and its inputs of production. Two specifications have been considered for the firm-specific production function, both based on gross output and three inputs (labour, capital, and intermediates): a Cobb-Douglas production function and a Translog production function. Therefore, for a given firm in a specific industry, the following production functions have been considered:

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

in the case of a Cobb- Douglas production function, and

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lm} l_{it} m_{it} + \beta_{lk} l_{it} k_{it} + \beta_{mk} m_{it} k_{it} + \omega_{it} + \varepsilon_{it} \quad (3)$$

in the case of a Translog production function. In both cases, is the log of deflated firm level gross output and l_{it}, m_{it}, k_{it} are, respectively, (log) labour, intermediates, and capital, while omega is productivity and epsilon is the error term. The Cobb-Douglas can be considered a special case of the Translog, when all the higher order and the interaction terms are equal to zero.

Both production functions have strengths and weaknesses when used to estimate mark-ups. For the Cobb Douglas production function no variation in output elasticities exists across firms within the same industry and, consequently, variation in mark-ups over time and producers is driven by that of revenue shares. The Translog production function, instead, retrieves firm-level output elasticity estimates and, consequently, mark-ups variation is given by firm-level variation in both revenue shares and output elasticities. The output elasticity of interest is, indeed, given by the first derivative of (2) and (3) with respect to the intermediate input. In the first case, this is simply $\hat{\beta}_m$, which is common to all firms of a given sector; in the second case, instead, the derivative with respect to intermediates is $OE_{it}^m = \hat{\beta}_m + 2\hat{\beta}_{mm}m_{it} + \hat{\beta}_{lm}l_{it} + \hat{\beta}_{mk}k_{it}$, which is firm specific. A firm specific value for the output elasticity implies that each firm is likely to combine inputs of production in a different way. However, the values obtained with the Cobb-Douglas are simpler to estimate and, as a consequence, generally considered more stable in the literature than those obtained through the Translog¹. Using expression (1) and the estimates for output elasticity, mark-ups can therefore be computed².

3. Data and descriptive statistics

3.1. The sample

The analysis carried out in this paper requires two types of information: accounting data on firms, and a measure of digital penetration in sectors. The firm-level data are sourced from the commercial dataset Orbis® by Bureau van Dijk (BVD). It provides information on firms' localisation, annual balance sheet and income statements, although the number of observations per country can vary significantly. It covers the period 2001-14 for 26 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, Turkey, the United Kingdom, United States.

BVD sources these data from a variety of suppliers, from credit rating agencies to national central banks. 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), estimation of key economic variables (mainly, Multi Factor Productivity), and extensive cleaning to net out the influence of measurement error and extreme values in the analysis³. As sampling strategies and reporting threshold vary across the underlying data sources, concerns over the representativeness of the dataset at the economy level over time may arise. To limit such concerns, only firms displaying on average at least 20 employees over the period were considered in the analysis. Many countries included in Orbis, indeed, report exclusively data for firms with more than 20 employees or only a limited sample for firms under this threshold. Therefore, the exclusion of firms under this threshold guarantees a better homogeneity and comparability across countries. Current analysis comparing administrative data sources and Orbis confirms indeed that for the group of firms employing more than 20 workers, Orbis covers a larger portion of the population of firms than for the sample including firms of all sizes (for a technical paper examining the representativeness of Orbis, see Bajgar et al., forthcoming). In addition, as mark-ups are generally increasing with firm size (see for example De Loecker and Eeckhout, 2017), this restriction on the sample should not affect the qualitative conclusions of the analysis⁴. Further concerns on the accuracy of Orbis data may relate to differences in the reporting units and accounting requirements across countries. For instance, Orbis reports mostly consolidated data for U.S. firms, and both consolidated and unconsolidated data for European ones. While this results in a less satisfactory coverage of the U.S. vis-à-vis European countries, the proposed analysis only exploits consolidated data, which fits the object of the analysis and limits the scope of biases in cross-country comparisons.

The final sample was further restricted to manufacturing and non-financial market service sector firms, for which the estimation of Multi Factor Productivity can be carried out on the basis of the reported financial information. Utilities (ISIC rev. 4 industries 35 to 39), construction (41 to 43), and real estate activities (68) were also excluded⁵.

Table 1. Summary statistics in 2005 industry-level USD PPP, overall

Variable	Mean	Median	SD	N. of obs
Real Gross Output ('000)	51 300	11 700	411 000	2 508 619
Real Value Added ('000)	13 400	2 988	139 000	2 508 619
Real Intermediates ('000)	27 100	5 495	192 000	2 508 619
Number of employees	178	50	1,341	2 508 619
Real Capital Stock ('000)	21 200	1 903	374 000	2 508 619
Log(Mark-up): Cobb-Douglas	0.30	0.22	0.30	1 803 377
Log(Mark-up): Translog	0.97	0.89	0.28	2 152 650

Source: Author's estimations on Orbis® data.

Table 1 reports selected summary statistics for the variables used to compute the production function and, finally, mark-ups. As stated above, only those observations reporting all the necessary variables to compute productivity were kept. In addition, as is standard in the literature, the top and bottom 3% of the distribution of mark-ups was trimmed, in order to be sure that the estimates are not affected by outliers⁶.

3.2. Overview of the digital intensity taxonomy by sector

The second fundamental source of information is the degree of digital intensity of sectors. As the digital transformation unfolds, it affects sectors differently, depending on their rate of adoption of the new technologies and business practices. Recent OECD work (Calvino et al., forthcoming) benchmarks sectors by their degree of digital intensity over the period 2001-15. It looks at digitalisation in its various manifestations, and in particular its technological components (here: tangible and intangible ICT investment, purchases of intermediate ICT goods and services, robots), the human capital it requires to embed technology in production (ICT specialists intensity), and the way it changes the interface of firms with the output market (online sales). 36 ISIC rev. 4 sectors (as in the OECD Structural Analysis (STAN) dataset) are thus ranked by their intensity in these dimensions. Figure A.1 displays these sectors by quartile of digital intensity for the period 2013-15, for each of the considered indicators. It shows that some sectors lag behind in the extent to which they have undergone the digital transformation, no matter the type of indicator used to measure such a transformation (agriculture, mining, real estate), while others rank consistently at the top of the distribution (telecom and IT services).

Lastly each sector gets attributed a single value across all the considered dimensions, and a quartile of the digital intensity distribution as a consequence. This is done for the end period of the sample (2013-15) and the starting period (2001-03), to capture changes in the digital intensity of sectors over time.

The taxonomy of sectors can be used to assess whether market power is different across digital intensive and less digital intensive sectors. It remains, however, an approximate picture of the penetration of digitalisation in the economy, as the phenomenon has more dimensions than are captured by our taxonomy. Importantly, a characterisation by industrial sector fails to capture the within-sector heterogeneity in adoption of digital technology. Unfortunately, Orbis data does not report sufficient information on the technologies firms embed in production, thus making a within-industry analysis impossible.

In Table 2 the same summary statistics as in Table 1 are reported, but dividing the sample into digital intensive and less digital intensive sectors, for the two periods for which the digital binary

variable is available (2001-03 and 2013-14). The last column, “Diff” reports the statistical significance of the difference between the mean value of the variable in digital intensive sectors vs. the mean in less digital intensive sectors, as assessed by a two-sided t-test. All means are statistically different across samples.

Table 2. Summary statistics 2005 industry-level USD PPP, by digital intensity

Variable	2001-03, less digital intensive				2001-03, digital intensive				Diff.
	Mean	Median	SD	N.Obs	Mean	Median	SD	N.Obs	
Real Gross Output ('000)	32 600	8 935	306 000	147 103	52 300	12 300	406 000	237 782	***
Real Value Added ('000)	9 292	2 625	109 000	147 103	13 400	2 864	147 000	237 782	***
Real Intermediates ('000)	15 800	3 785	132 000	147 103	29 200	6 027	213 000	237 782	***
Number of employees	137	47	1 492	147 103	193	48	1 379	237 782	***
Real Capital Stock ('000)	13 700	2 224	176 000	147 103	18 000	1 453	478 000	237 782	***
Log(Mark-up): Cobb-Douglas	0.27	0.23	0.20	120 791	0.29	0.20	0.29	189 798	***
Log(Mark-up): Translog	0.94	0.91	0.16	140 050	0.96	0.87	0.29	225 637	***
Variable	2013-14, less digital intensive				2013-14, digital intensive				Diff.
	Mean	Median	SD	N.Obs	Mean	Median	SD	N.Obs	
Real Gross Output ('000)	45 400	8 364	539 000	131 268	70 300	14 300	534 000	217 449	***
Real Value Added ('000)	12 000	2 525	202 000	131 268	17 900	3 555	169 000	217 449	***
Real Intermediates ('000)	23 000	4 100	227 000	131 268	38 000	7 066	264 000	217 449	***
Number of employees	154	50	1 470	131 268	219	56	1,457	217 449	***
Real Capital Stock ('000)	27 300	2 459	569 000	131 268	31 100	1 777	485 000	217 449	**
Log(Mark-up): Cobb-Douglas	0.31	0.26	0.26	103 797	0.34	0.21	0.36	167 776	***
Log(Mark-up): Translog	0.97	0.93	0.20	122 068	1.01	0.88	0.35	202 830	***

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

On average all variables have increased from the initial to the final period, both in the intensive and less intensive digital sectors. Moreover, firms belonging to digitally-intensive sectors are on average bigger (in terms of number of employees, real value added, or real gross output) and exhibit higher mark-ups. Finally, the difference in average mark-ups of firms belonging to digital intensive and less digital intensive sectors has increased over time.

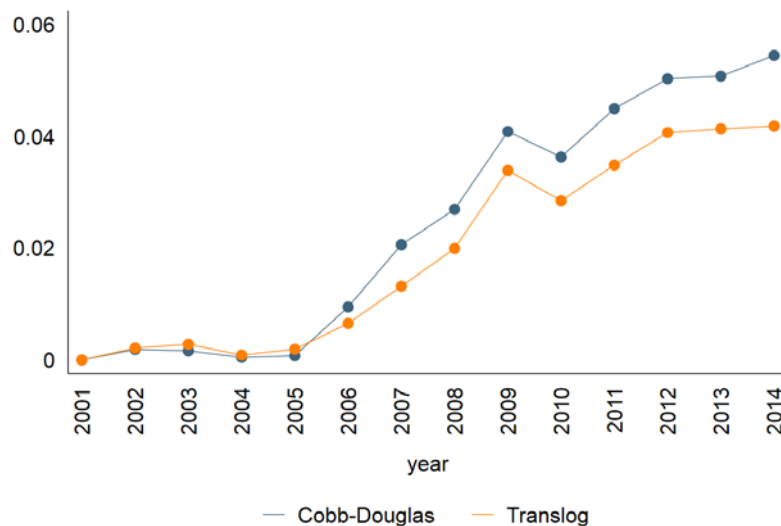
4. Results

4.1. Evidence on rising mark-ups

As stated in the introduction, in this project market power has been approximated with mark-ups. In a theoretical, perfectly competitive market, no actor has the power to affect market prices; firms enter while positive profits can be made and firms price their products at their marginal cost as a consequence. Mark-ups, defined as the ratio of unit price over marginal cost, are thus equal to unity. If markets instead are not perfectly competitive, firms can charge consumers a price higher than the marginal cost, leaving a positive wedge between them and a mark-up greater than unity.

The analysis shows that mark-ups have been increasing over time over the period 2001-14 in the sample. Figure 1 plots the average growth rate of mark-ups over time, for both production function specifications. The figure shows that mark-ups have been increasing by around 6% (4%) over the period considered when using a Cobb-Douglas (Translog) production function. A similar increase is also reported in a recent study by De Loecker and Eeckhout (2017), who estimate mark-ups over a longer time horizon for publicly-traded companies in the United States. Reassuringly, the two production functions exhibit very similar patterns over time⁷.

Figure 1. Average of firm log mark-up: growth 2001-14.



Note: Unconditional averages of firm-level 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.

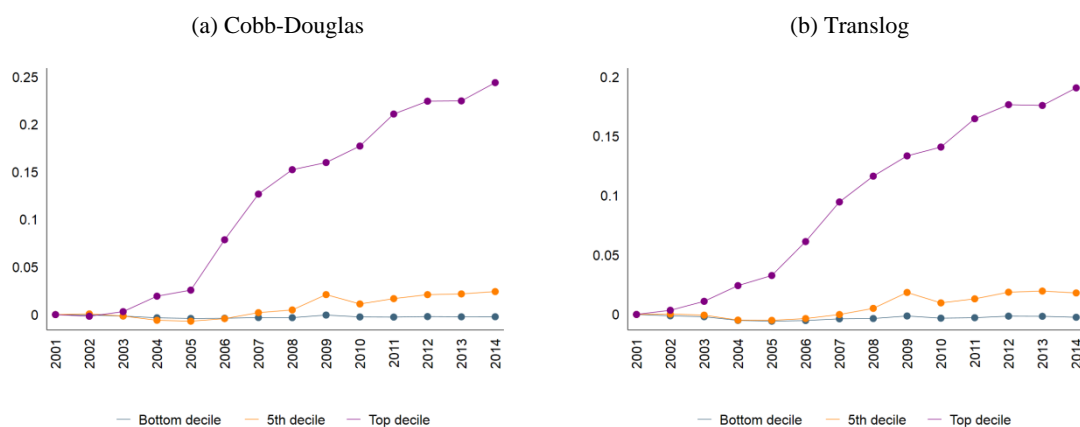
Source: Author's estimations on Orbis® data.

Interestingly, once firms are grouped by their mark-up levels⁸, 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). Note that deciles of the distribution are defined relative to the rest of the firms in each particular year. This choice is explained by the aim of describing changes in the business environment over time rather than focusing on changes for specific firms. In fact, the analysis investigate to what extent differences between firms in business today vs firms in business a decade ago can be attributed to the digital transformation. Thus the firms included in the top decile may change from year to year.

Figure 2 plots average growth rates of mark-ups over time in the top, the bottom and the median decile of the mark-ups distribution (in the left panel the underlying production function is a Cobb-Douglas, whereas in the right panel a Translog). In both cases, while the bottom and the median decile exhibit a flat trend, the top decile increases over time by around 20%. Said differently, this analysis suggests that it is the case that firms with the highest levels of market power enjoy increasingly larger mark-ups vis-à-vis firms belonging to rest of the mark-up distribution. The average mark-up growth depicted in Figure 1 seems, therefore, to be mainly driven by firms exhibiting the highest mark-ups.

To sum up, looking at trends of mark-ups over time: i) on average, mark-ups are increasing over the period 2001-14; ii) this result seems to be driven by those firms that enjoy the highest level of mark-ups, the bottom half of the mark-ups distribution exhibiting essentially a flat trend over time. One of the potential criticisms to the analysis might be that the trends depicted above hinge upon the inclusion of single countries. Robustness checks performed eliminating the U.S. from the sample show the same patterns.

Figure 2. Log Mark-up growth over time (2001-14) in different parts of the distribution.



Note: Unconditional averages of firm-level log mark-ups in the chosen part of the distribution of mark-ups. 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.

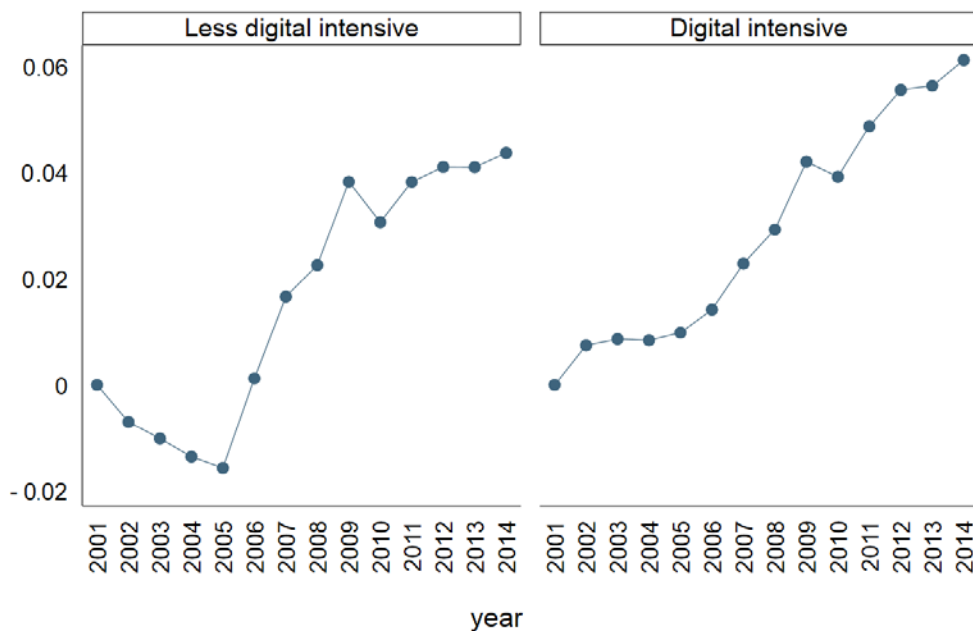
Source: Author's estimations on Orbis® data.

4.2. The digital transformation and market power

This section explores whether mark-ups differ between sectors defined as digital intensive and less digital intensive. Figure 3 and A.2 presents evidence that firms operating in sectors which are defined as digital intensive at the beginning of the period (right hand side of the figure) display by the end of fourteen years a higher average growth in mark-ups than firms operating in less digital intensive sectors. The growth differential is larger when a Translog production function is considered (figure A.2)⁹.

These descriptive facts, however interesting, may be driven by other factors which differ across digital intensive and less digital intensive sectors, and which are related to mark-ups themselves. Some of these factors are taken into account below, where the econometric analysis aims at teasing out the “true” relationship between a sector’s digital intensity and firms’ mark-ups from other confounding factors. Two main trends emerge: first, firms in the top-digital sectors are found to display on average higher mark-ups than firms operating in low-digital sectors. Second, the gap in mark-ups between the average firm in a top-digital vs bottom-digital sector is larger in 2013-14 than in 2001-03, suggesting that this positive correlation between mark-ups and digitalized sectors is stronger nowadays than in the past¹⁰.

Figure 3. Mark-up growth over time (2001-14) in digital intensive vs less digital intensive sectors



Note: The distinction between digital intensive sectors (resp. less digital intensive sectors) rank above (resp. below) the median sector by digital intensity, as calculated jointly over all indicators of digitalisation in Calvino et al. (forthcoming). This graph fixes the ranking of sectors to the initial period (2001-03), and shows only mark-ups estimated assuming a Cobb-Douglas production function.

Source: Author’s estimations on Orbis® data.

These facts are presented in Figure 4 (see the corresponding Table A.1 in the Appendix) which reports differences in mark-ups for firms operating in digital intensive sectors relative to less digital intensive sectors conditional on other firm characteristics, such as age, size, and country-year of operation. Sectors are classified as “digital”, if their digital intensity is above the median of all sectors (e.g. publishing, audiovisual and broadcasting activities; wholesale and retail trade, repair of motor vehicles and motorcycles; and computer, electronic and optical products) and as “top-digital” if they are in the top quartile of the sector distribution in terms of digital intensity (e.g. telecommunications and IT and other information services)¹¹. Differences between Translog and Cobb-Douglas coefficients are not driven by differences in the sample composition¹². Future work will further explore whether the first decile of the mark-up distribution is composed by ever-changing companies, or always the same set of companies, and whether the top firms by mark-up are also displaying the highest productivity. Both perspectives could help better understand whether and how digital technologies may have been changing the market structure in OECD countries.

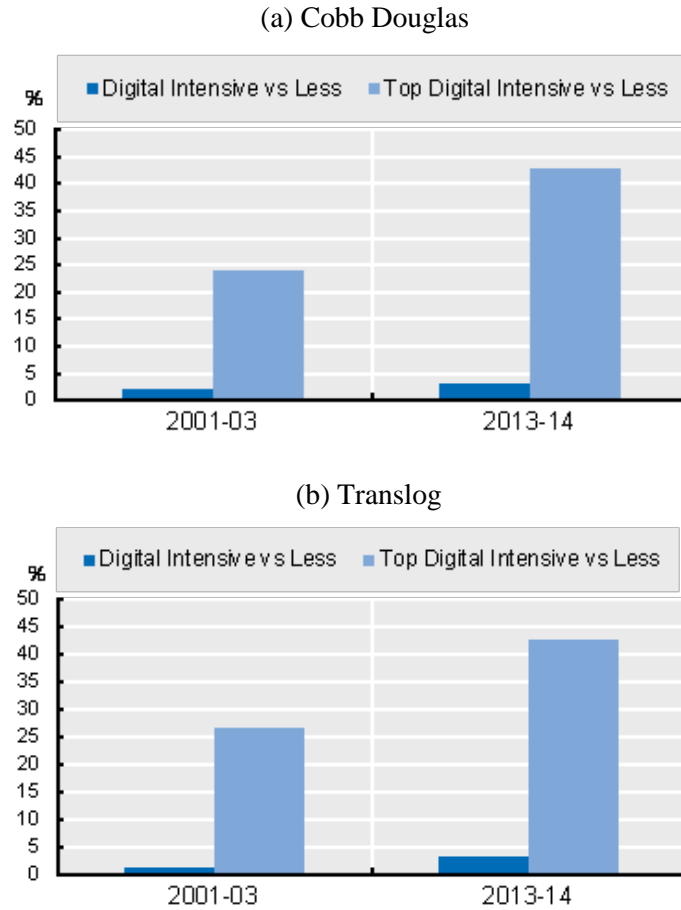
The estimates suggest that firms operating in a “digital intensive” sector enjoy a 2 to 3% higher mark-up than firms operating in less digital intensive sectors, and that this gain is substantially higher (up to 43%)¹³ if a firm is operating in one of the top digital sectors. Second, Figure 4 compares these differentials over time: not only the magnitude of the gains in mark-up grows over time (dark blue vs light blue bar) but the extent to which this gap has increased over time is much more significant for firms in sectors that are most digital intensive. The results hold and are quantitatively very similar when mark-ups are estimated assuming a Cobb Douglas or a Translog production function, as reported in Panel (b) of the Figure.

To summarise, four basic results have been presented from an initial analysis of mark-ups in firms from 2001-14. Looking at mark-ups generally, two trends emerge: (i) average mark-ups are increasing over time; (ii) these trends are mainly driven by a steep increase in mark-ups of the top decile of firms. Distinguishing between digital intensive and less digital intensive sectors, it is observed that: (iii) mark-ups are higher in digital intensive sectors than in less digital intensive sectors; (iv) mark-up differentials between digital intensive and less digital intensive sectors have increased significantly over time.

These facts seem to suggest that market mechanisms in the considered economies may have been changing relative to the paradigm of free-markets. Other recent studies suggest similar findings, starting from the mentioned De Loecker and Eeckhout (2017), Bessen (2017), Grullon et al. (2017) and McKinsey Global Institute (2015a,b).

The analysis however has retrieved associations which cannot yet 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. This concern, however, is partly reduced in this analysis by the consideration of multiple dimensions of the digital transformation, some of which may not rely too heavily on the availability of high market power to be embedded in production (e.g. the hiring of an ICT specialist). Furthermore, the digital taxonomy is defined at the sectoral level, which should lessen the scope for the reverse causality, which might be more of a concern if the measure of digital intensity was expressed at the firm level. Lastly, as already mentioned, in one of the performed robustness checks changes in mark-ups in the final period were correlated with the digital intensity of sectors in the initial period. The direction and magnitude of the association stay essentially the same, despite the significantly lower reverse causality concerns.

Figure 4. Average percentage differences in mark-ups between firms in less digital intensive and in digital intensive sector 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, on the basis of the company's size, age and country-year of operation, as well as a dummy variable with value 1 if the sector of operation is digital intensive vs less intensive (specifications on the left in the graph), or if the sector of operation is among the top 25% of digital intensive sectors vs not (specifications on the right in the graph). Panel (a) estimates mark-ups based on a Cobb Douglas production function, (b) on a translog production function. Standard errors are clustered at the company level. All coefficients are significant at the 1% confidence level.

Source: Author's estimations on Orbis® data.

5. Discussion and conclusions

Markets rarely correspond to the theoretical textbook case of perfect competition where prices equalize firms' marginal costs and no market power exists. This is especially the case when products are heterogeneous, i.e., multiple varieties exist for the same product, and consumers can perceive them as at least slightly different one from the other. A high level of product differentiation (and customisation to the client's needs) is typical of services, which nowadays account for the majority of GDP in OECD countries. Second, some temporary restriction of competition, e.g. the one granted to innovators by patents, might be needed ex-ante to strengthen innovators' incentives for investment. Third, some market power may be generated by products of higher quality, and the branding strategies of firms.

More generally, the balance between fostering ex-ante the introduction of new products and new services, which could satisfy consumers' preferences and promote economic growth, and concerns of lack of competition ex-post, has always been difficult to strike. This is all the more true in the digital economy because of network effects.

The present analysis focuses on one aspect of the competitive environment, i.e., the dynamics of firm mark-ups. The richness of the firm-level data and the flexibility of the methodology chosen allow for a differential analysis of mark-ups along the distribution and across firms with different characteristics, such as size or age. It finds increasing mark-ups on average across all firms in the sample, similarly to what De Loecker and Eeckhout (2017) found for the U.S. It further shows that mark-ups are higher and have grown more in digital intensive sectors than in less digital intensive sectors over the 2001-14 period.

That said, further refinements of the mark-up measures and additional robustness tests are envisaged to confirm and extend these novel empirical results. The proposed taxonomy of sectors by digital intensity is an imperfect proxy of the phenomenon, which entails a broader set of dimensions than those considered in the taxonomy. The analysis could benefit from (i) consideration of how intensive sectors are in homogeneous or heterogeneous goods and services; access to information on (ii) technology adoption at the firm level; (iii) the importance of network effects at the sectoral level and (iv) at the firm level and finally (v) the role of intangible assets in explaining the observed patterns in mark-ups. A second extension of the present analysis could control for the firm's innovation output (patents), which is likely to be a well-established source of market power. Martins et al. (1996), for instance, correlate average industry mark-ups with the R&D intensity of the sector.

It is also possible that some firm- and industry-level characteristics which are not explicitly treated in our empirical model are both generating higher mark-ups, and allowing for a sector to leap ahead in the digital transformation. One such dimension is indeed the firm's ability to innovate. A second such dimension would be the level of exposure of the sector to international competition. Technology adoption, innovation and international linkages are all linked to a firm's productivity.

Lastly, as mentioned, mark-ups are but one possible measure of market power, albeit a very meaningful one used widely in the literature. Future work could expand the analysis of the competitive environment by looking at other proxies of imperfect competition aside from mark-ups, such as profits, market concentration and M&A activities.

Notes

1 The parameters of the production function are estimated econometrically at the firm-level using the Akerberg, Caves and Frazer (2006) control function approach (known as the ACF approach), while relying on material demand to proxy for productivity. This is a two-stage approach in which all parameters are estimated in the second stage. This point is particularly important when estimating more flexible production functions, such as the Translog, since the identification of the labour coefficient in the first stage relies heavily on the assumptions underlying the control function. Issues related to the stability of estimated values for the production function may play a role in the differences between Cobb-Douglas-based vs Translog-based mark-ups (see below). For a detailed discussion of control function approaches, see Akerberg et al. (2007).

2 As discussed in De Loecker and Warzynski (2012), the expenditure share for intermediates, μ , has to be corrected for measurement error in output, y , obtained in the first stage of the ACF procedure. This correction is meant to eliminate any variation in μ that comes from variation in output not related to variables impacting input demand, i.e., unanticipated shocks to production which are unknown to the firm when it decides on how to optimise input use.

3 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.

4 As shown later in the paper, the average increase in mark-ups uncovered in the analysis reflects mostly an increase in mark-ups of the top decile of the mark-ups distribution. In unreported analysis, available upon request, the probability of being in the top decile was related to the size of the firm in terms of employment. Two alternative specifications were tested. In the first specification, firm size was included log-linearly, while in the second size was expressed as categorical variable, where the categories are 20-49; 50-99; 100-249; 250-499, 500-999, 1 000+. In both specifications, a higher firm size is linked to a significantly higher probability of being in the top decile of the mark-up distribution.

5 See detailed list of sectors in Appendix (Table A.2).

6 The analysis excludes outliers in the top and bottom 3 percent of the mark-up distribution to ensure that the results are not driven by outliers following for example De Loecker et al., (2016), see their footnote 50. However, exactly as they suggest, the results of the present analysis were found robust to alternative trimming choices (top and bottom 1% or 5%). More generally, in studies using firm level data it is common practice to delete outliers. See for example Hall and Mairesse (1995) or Hsieh and Klenow (2009).

7 The levels of mark-ups are however slightly different when estimated assuming a Cobb-Douglas or Translog production function. This is likely due (i) the existence of remaining outliers in the measure of deflated materials, which enter directly the computation of the output elasticity in Translog but not Cobb-Douglas; and (ii) the stability of estimated parameters of the production function, greater when this is Cobb-Douglas than Translog. De Loecker and Eeckhout (2017) observe a difference in the level of mark-ups computed through the Cobb-Douglas and the Translog production functions of very similar magnitude to the one presented here above for the

same period. They also stress that “The only difference is in the actual level of the mark-up, which is not direct interest, while the change over time is again very similar”.

8 In each 1-digit sector, firms were divided into 10 deciles over the mark-up distribution. For example, the 10% of firms with the highest mark-ups belong to the “Top decile”, whereas the 10% of firms with the lowest mark-ups belong to the “Bottom decile”. In Figure 2, the average across all countries and sectors is plotted year by year for the top, the median, and the bottom decile of the distribution.

9 In unreported analysis, available upon request, a regression was run with log mark-ups as dependent variable on year dummies and year dummies interacted with the digital (top digital) dummies. The interacted terms were all positive and statistically significant (with the exception of that for 2009 for the digital sample, where the coefficient is significant only at the 13% level). This confirms the difference in trends shown in Figure 3.

10 This conclusion is drawn from comparing the point estimates of interaction terms and their statistical significance.

11 It means that the “top-digital” sectors are also included in the “digital” category; in particular, sectors above the median in the “digital” category are also classified as “top-digital”. A further robustness specification checks whether differences in mark-ups for firms operating in digital intensive sectors relative to less digital intensive sectors are mainly driven by: (i) the top quartile relative to the third quartile; (ii) the top decile of sectors. The results are indeed driven by the top quartile sectors. Moreover, including a dummy for the top decile separately from the rest of the top quartile sectors yields significantly larger coefficients for the very “top” group, while both terms remain statistically significant. These results are available upon request.

12 Further omitted robustness checks retrieve qualitatively similar pattern for the samples: (i) excluding the United States; (ii) G20 vs non-G20 countries; (iii) fixing the digital intensity classification to the first period also in final-period regressions, similar to what done in Fig.3; (iv) restricting the sample to firms which display both specifications of mark-ups; (v) excluding firms which exist throughout the period, which are bound to be significantly different from those which do not. A final specification investigates the robustness of the results to possible omitted variables including in the baseline a firm-level and sectoral-level capital intensity control.

13 $43\% = \exp(1+0.36) - 1$. See Halvorsen and Palmquist (1980).

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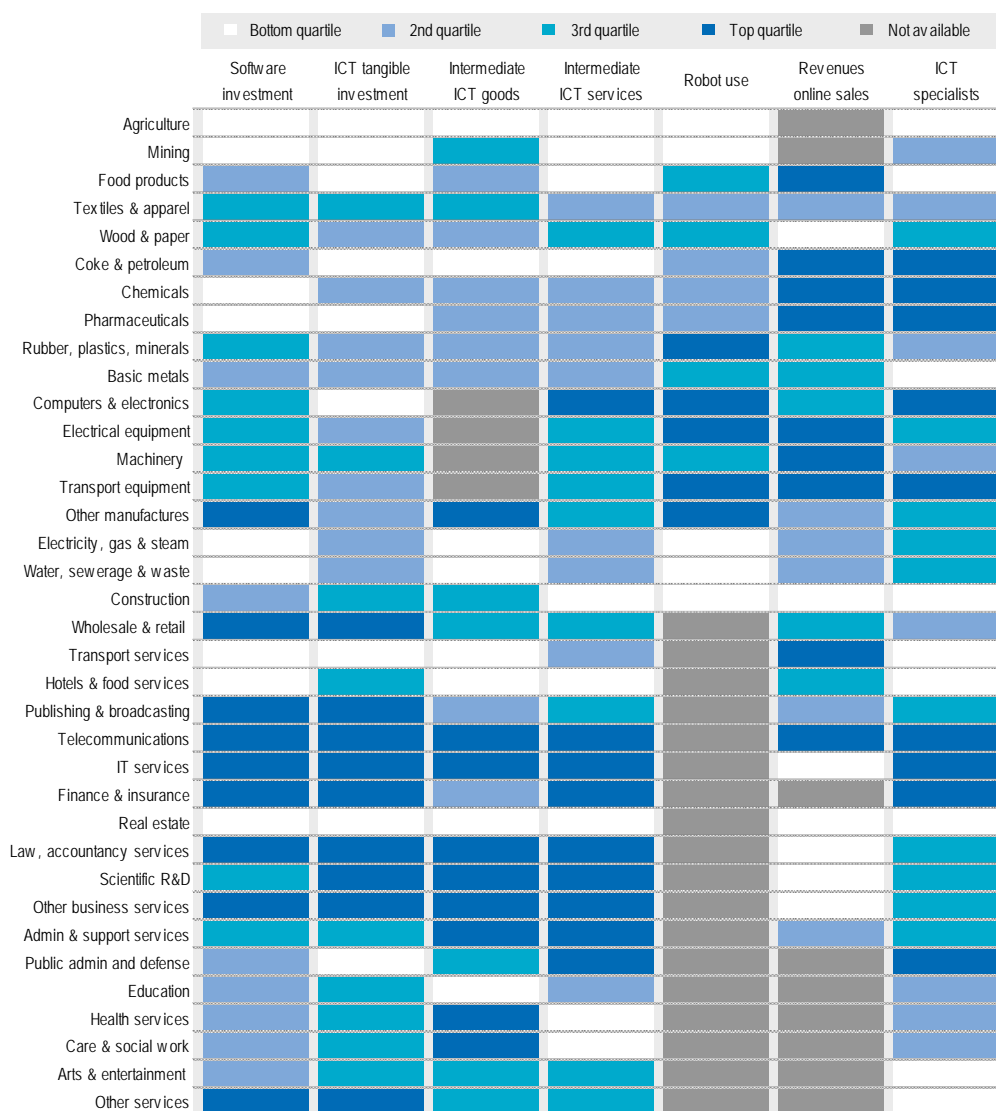
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Annex

Figure A.1. Taxonomy of sectors by quartile of digital intensity, 2013-15



Note: All underlying indicators are expressed as sectoral intensities. For each indicator, the sectoral 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 sectors and years are non-missing, with the exception of robot use and online sales, where some sectors are not sampled.

Source: Science, Technology and Innovation Scoreboard 2017 (forthcoming), 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.

Table A.1. Baseline regressions

	2001-03				2013-14			
	Cobb Douglas		Translog		Cobb Douglas		Translog	
Digital intensive	0.019***		0.013***		0.029***		0.033***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Top digital intensive		0.215***		0.237***		0.355***		0.354***
		(0.002)		(0.002)		(0.002)		(0.002)
Log(Age)	-0.054***	-0.035***	-0.050***	-0.030***	-0.086***	-0.047***	-0.076***	-0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log(L)	0.037***	0.024***	0.072***	0.056***	0.044***	0.019***	0.076***	0.049***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	308 157	308 157	363 027	363 027	266 624	266 624	319 685	319 685
R-squared	0.060	0.184	0.094	0.254	0.088	0.473	0.106	0.441

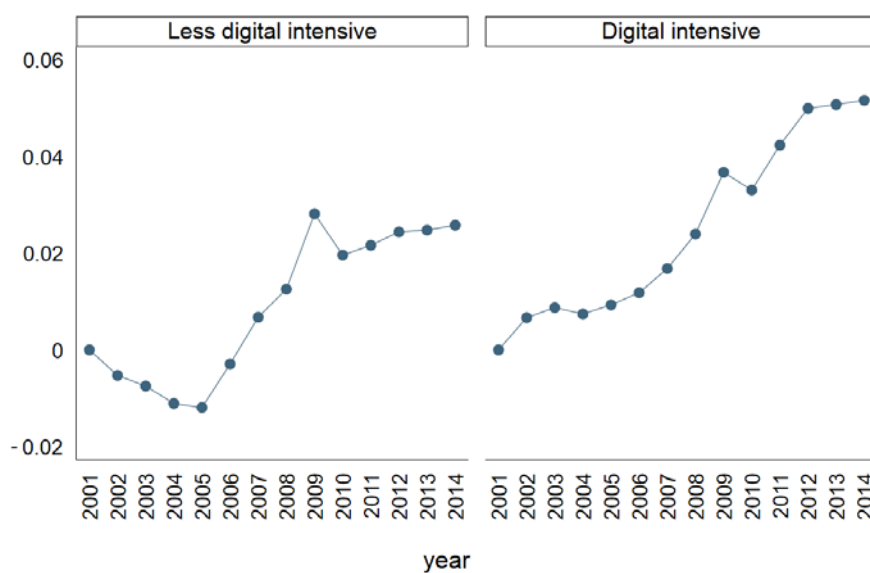
Note: Results of estimating OLS regressions where the dependent variable is a firm's log-mark-ups. "Digital intensive" is a dummy variable with value 1 if the sector is above the median of all 36 considered sectors by digital intensity, as ranked in Calvino et al. (forthcoming). "Top digital intensive" is a dummy variable with value 1 if the sector is in the top quartile of digital intensity instead. Errors are clustered at the company level. *** p<0.01, ** p<0.05, * p<0.1.

Source: Author's estimations on Orbis® data.

Table A.2. ISIC rev.4 2-digit code and broad description

D10T12 Food products, beverages and tobacco [CA]
D13T15 Textiles, wearing apparel, leather and related products [CB]
D16T18 Wood and paper products, and printing [CC]
D20 Chemicals and chemical products [CE]
D21 Basic pharmaceutical products and pharmaceutical preparations [CF]
D22T23 Rubber and plastics products, and other non-metallic mineral products [CG]
D24T25 Basic metals and fabricated metal products, except machinery and equipment [CH]
D26 Computer, electronic and optical products [CI]
D27 Electrical equipment [CJ]
D28 Machinery and equipment n.e.c. [CK]
D29T30 Transport equipment [CL]
D31T33 Furniture; other manufacturing; repair and installation of machinery and equipment [CM]
D45T47 Wholesale and retail trade, repair of motor vehicles and motorcycles [G]
D49T53 Transportation and storage [H]
D55T56 Accommodation and food service activities [I]
D58T60 Publishing, audiovisual and broadcasting activities [JA]
D61 Telecommunications [JB]
D62T63 IT and other information services [JC]
D69T71 Legal and accounting activities; activities of head offices; management consultancy activities; architecture and engineering activities; technical tests
D72 Scientific research and development [MB]
D73T75 Advertising and market research; other professional, scientific and technical activities; veterinary activities [MC]
D77T82 Administrative and support service activities [N]

Figure A.2. Mark-up growth over time (2001-14) in digital intensive vs less digital intensive sectors using Translog specification



Note: The distinction between digital intensive sectors (resp. less digital intensive sectors) rank above (resp. below) the median sector by digital intensity, as calculated jointly over all indicators of digitalisation in Calvino et al. (forthcoming). This graph fixes the ranking of sectors to the initial period (2001-03), and shows only mark-ups estimated assuming a Translog production function.

Source: Author's estimations on Orbis® data.