INSTITUTE
OF ECONOMICS

Scuola Superiore
Sant'Anna

LEM | Laboratory of Economics and Management

Institute of Economics
Scuola Superiore Sant'Anna

Piazza Martiri della Libertà, 33 - 56127 Pisa, Italy
ph. +39 050 88.33.43
institute.economics@sssup.it

LEM

WORKING PAPER SERIES

Cloud technologies, firm growth and industry concentration: Evidence from France

Bernardo Caldarola [1]
Luca Fontanelli [2]

[1] UNU-MERIT and Maastricht University, Maastricht, the Netherlands, and Enrico Fermi Research Center, Rome, Italy
[2] University of Brescia, Italy, and RFF-CMCC European Institute on Economics and the Environment, Milan, Italy

2024/25 September 2024
ISSN(ONLINE) 2284-0400

Cloud technologies, firm growth and industry concentration: Evidence from France

Bernardo Caldarola[1,2] and Luca Fontanelli[3,4,*]

[1]UNU-MERIT and Maastricht University, Maastricht, the Netherlands
[2]Enrico Fermi Research Center, Rome, Italy
[3]Università di Brescia, Italy
[4]RFF-CMCC European Institute on Economics and the Environment
[*]Corresponding author: luca.fontanelli@unibs.it

September 27, 2024

Abstract

Recent empirical evidence finds positive associations between digitalisation and industry concentration. However, ICT may not be all alike. We investigate the effect of the purchase of cloud services on the long run size growth rate of French firms. Our findings suggest that cloud services positively impact firm growth rates, with smaller firms experiencing more significant benefits compared to larger firms. This evidence suggests that the diffusion of cloud technologies may help mitigate concentration in the era of the digital transition by favouring the digitalisation and growth of smaller firms, especially when the cloud services provided are more advanced.

Keywords: cloud, ICT, concentration, firm growth rate, firm performance.
JEL Codes: L20, L25, O33

1 Introduction

Recent studies have established a positive association between digitalisation and intangible assets on one side, and industry concentration on the other (see e.g., Bessen 2020, Bajgar et al. 2021, Lashkari et al. 2024), showing that the use of information and communication technologies (ICT) benefits larger firms to a greater extent (Brynjolfsson et al. 2023, Babina et al. 2024). However, ICTs may not be all alike. In particular, cloud computing services promote key organisational changes within firms by substituting the costly IT investments complementary to several digital technologies (Bloom & Pierri 2018), such as AI (see also McElheran et al. 2023, Calvino & Fontanelli 2023*b*). Furthermore, its use allows firms to expand operations with fewer constraints (see Jin & McElheran 2019), scaling their production without requiring large investments in IT assets (Brynjolfsson et al. 2008) and producing positive effects on both size and productivity (Gal et al. 2019, Duso & Schiersch 2022, Jin 2022). This positive link has been found to be more pronounced for younger firms (Bloom & Pierri 2018, Jin & McElheran 2019, DeStefano et al. 2023), suggesting that these firms disproportionately benefit from the use of cloud services by gaining access to otherwise inaccessible IT complementary assets.

Yet, to our knowledge, there is no evidence exploring whether also smaller firms enjoy higher benefits from cloud use than larger firms, conditional on age. First, small firms may struggle to invest into IT assets and to navigate through the current digital paradigm. Cloud technologies represent a crucial service for these firms as it lowers the fixed costs of digitalisation, allowing to store data and files, operate software and undertake computationally intensive activities without owning the underlying physical IT facilities. Second, the purchase of cloud services in a market dominated by few large providers (e.g., Google and Amazon) implies the existence of positive markups on the cost of using providers' IT assets via cloud service. This suggests that, when the need for IT assets is compelling as it is the case for large firms, the purchase of cloud services may not be cost-effective.

In this work, we explore the heterogeneous impact of cloud technologies on the size growth rate of firms based on a unique combination of four sources of micro data for French firms between 2005 and 2018 – French ICT surveys (2016 and 2018), administrative data from French firms' balance sheets (2005–2019), French matched employer-employee data (2005–2019) and the French business register (2005–2019). We focus on long run growth rates, in line with the idea that the effects of digital technologies may take time to materialise due to large and complex organisational changes characterised by uncertainty and implementation lags (Brynjolfsson & Hitt 2003, Brynjolfsson et al. 2018, Acemoglu & Restrepo 2020).

We find that cloud has a positive relationship with the growth rates of firms, which is less pronounced for large firms. We address potential endogeneity issues by adopting a causal identification strategy based on an endogenous treatment model (ET henceforth, see Heckman 1976, 1978, Maddala 1983, Vella & Verbeek 1999), where the purchase of cloud services is our endogenous treatment variable. This latent variable model is widely used in research (e.g., Shaver 1998, King & Tucci 2002, Campa & Kedia 2002) as it addresses the issue of self-selection of firms into treatment (Hamilton & Nickerson 2003, Clougherty et al. 2016). We employ lighting strikes per capita at the municipality (French commune) level, a source of spatial exogenous variation associated to investments in IT infrastructure (also see Andersen et al. 2012, Guriev et al. 2021, Caldarola et al. 2023), as the exclusion restriction variable. In order to adopt cloud technologies, firms need to have access to reliable, fast, and state-of-art internet connection (Nicoletti et al. 2020, Garrison et al. 2015, Ohnemus & Niebel 2016, DeStefano et al. 2023). However, by causing energy spikes and dips, lightning strikes may increase the maintenance costs of IT infrastructure, slowing down their diffusion (Andersen et al. 2012). Furthermore, lighting strikes lower the quality associated to broadband internet services, producing a four times larger frequency of broadband network failures during thunderstorms, if not adequately mitigated (Schulman & Spring 2011). Overall, our measure of lighting strikes per capita reflects the trade-off faced by internet providers who will have to balance the costs of expanding the broadband network and the potential benefits that can be harvested by expanding the network, given by the number of potential customers in each geographical area.

Results from the endogenous treatment models show that the purchase of cloud technologies has a positive effect on firms' long run growth rates. However, the effect diminishes for larger firms, suggesting that the diffusion of cloud services can help smaller firms narrow their size gap. This finding holds up across several robustness checks, including the change in the definition of size, the period wherein growth rates are computed, the econometric specification, and sample. Furthermore, when breaking down cloud purchases by specific applications – data and file storage, software use, and computational power -— we find that leveraging cloud technologies for more advanced applications (which are likely associated with higher fixed costs) tends to enhance the growth benefits of cloud adoption reaped by smaller firms.

We provide evidence of a possible mechanism explaining the heterogeneous effect of cloud on firm-level growth rates. Several works find that firms adopting digital technologies tend to be smaller (Zolas et al. 2020, Calvino & Fontanelli 2023*b*, Cirillo et al. 2023). We show that the purchase of cloud services by firms is positively linked to long run changes in digital intensity and that this relation tends to be stronger for smaller firms. Such evidence suggests that cloud services may be complementary to the use of other digital technologies, and the more so when firms are small, highlighting that cloud services purchase could grant the access to IT assets and boost the adoption of other digital technologies, positively affecting small firms' growth rates.

Finally, we examine whether the share of cloud-using firms and long run changes in concentration of individual industries are related by aggregating our data to the 2-digit sectoral level (see Brynjolfsson et al. 2023, Bessen 2020, Babina et al. 2024). Our analysis uncovers a negative correlation between the two, suggesting that the greater impact of cloud on size growth rate of smaller firms may mitigate increasing concentration trends (Bajgar et al. 2021).

Our findings have significant policy implications in the current context of increasing trends in industry concentration at play in many countries (see e.g., Bajgar et al. 2019, Grullon et al. 2019, Gutiérrez & Philippon 2017, Autor et al. 2020). ICT diffusion policies that support the digital transition could worsen the current state of competition, if they fail to differentiate between small and large firms, as ICT adoption has been linked to increased industry concentration (Brynjolfsson et al. 2023). However, our evidence suggests that smaller firms, which are generally less digitalised, have substantial untapped growth potential that could be unlocked through the broader diffusion of cloud technologies.

The remainder of the paper is organised as follows. Section 2 analyses the existing evidence on the use of cloud computing technologies by firms. Section 3 discusses the sources of data used for the analysis and reports key summary statistics. Section 4 describes the econometric framework and identification strategy applied in Section 5, where the main results of the analysis are reported. Section 6 estimates the cloud-concentration relation. Section 7 summarises the key findings and discusses possible avenues for future research.

2 Literature review

The OECD defines cloud technologies as *"a service model for computing services based on a set of computing resources that can be accessed in a flexible, elastic, on-demand way with low management effort"* (OECD 2014). The primary applications of cloud computing for firms involve the virtualisation of physical machines and software, and the provision of digital services as a local public utility. Some examples of cloud services include mailing software, file and data storage, online software, and access to computational power.

Fulfilling the early predictions put forward decades ago by ICT pioneers, cloud computing has revolutionised the acquisition of IT assets by firms and 'democratised' access to ICT for businesses (Bloom & Pierri 2018).[1] IT assets, whether physical (e.g., computers) or intangible

[1]In 1961, Professor John McCarthy predicted that *"computing may someday be organised as a public utility just as the telephone system is a public utility"*.

(e.g., ICT human capital), are indeed costly both in terms of money and time, with high fixed cost of adoption and large implementation lags (Brynjolfsson et al. 2018). However, these are needed by firms to reap the full benefits brought by digital technologies usage. In this respect, the purchase of cloud services – in place of IT investments – is an enabler for other digital technologies, due to prominent complementarities in the ICT domain. The purchase of cloud services is indeed associated with the use of other digital technologies (see Cho et al. 2022, DeStefano et al. 2022, Calvino & Fontanelli 2023*b*, Goos & Savona 2024). Yet, cloud services may not function as a 'prêt-à-porter' technology, so firms may incur in significant adoption costs. The use of cloud is indeed positively related with several complementary assets, including fast broadband availability, managerial quality, ICT skills, and IT capabilities (Nicoletti et al. 2020, Garrison et al. 2015, Ohnemus & Niebel 2016).

Notwithstanding the significant decline of cloud service prices in the 2010s (Byrne et al. 2018, Coyle & Nguyen 2018), the diffusion of cloud technologies appears to be still limited and heterogeneous across sectors (see Section 3.1 and Jin 2022). Furthermore, cloud users are larger, to some extent younger, and more digitalised (Zolas et al. 2020, Acemoglu et al. 2022). On the one hand, this evidence suggests the existence of large potential gains stemming from the adoption of cloud technologies by smaller firms in less digital-intensive sectors. On the other hand, it indicates relevant complementarities between cloud and other digital technologies. As a matter of fact, firms may use cloud because it complements various other digital technologies (e.g., AI) and facilitates leveraging physical IT capital, IT personnel, and data sharing across large facilities or within the same firm across different plants. This may underlie the observation that cloud users may not invest less in IT equipment (Duso & Schiersch 2022).

By substituting IT investments, the diffusion of cloud technologies promotes key organisational changes within firms (see the discussion in Jin & McElheran 2019). Their use allows a shift from a structure based on physical IT capital (assets ownership, high fixed costs, and irreversibility) to one based on intermediate IT costs (on-demand services, intermediate costs, and flexibility) – for example, from physical storage facilities to Google Drive services. Thanks to cloud computing, IT resources become easily accessible, scalable, and flexible for firms. Access to IT assets is on-demand and – virtually – does not imply any problem of capacity utilisation. Furthermore, the use of cloud services reduces the implementation lags of IT infrastructures and lowers maintenance costs. Economies of scale to the advantage of firms also increase, as they can leverage the same IT structure (e.g., data and IT personnel) beyond spatial borders.

For these reasons, positive effects in terms of both size and productivity at the firm level are expected to emerge from the diffusion of cloud technology adoption, as it allows scaling production without heavy investments in IT assets. This is referred to as the 'scale without mass' hypothesis: firms can expand operations with fewer constraints, thanks to the digitalisation of production (Brynjolfsson et al. 2008). It has indeed been found that the purchase of cloud services has a positive effect on users' size and productivity (Jin 2022, Duso & Schiersch 2022, Gal et al. 2019). Furthermore, this positive effect has been found to be more pronounced for younger firms (Bloom & Pierri 2018, DeStefano et al. 2023, Jin & McElheran 2019). In fact, younger actors may have a disproportionate advantage from the availability of cloud services due to improvements in access to IT resources and lower path dependency on pre-existing organisational settings?. This access is crucial as a complementary asset and may not be otherwise accessible for younger firms.

Yet, to our knowledge, there are no contributions to the literature exploring whether the positive effects of cloud services on firms are mediated by their size as well, conditional on age. However, the scope of cloud services may be larger in smaller firms, as they are less digitised (Zolas et al. 2020). Furthermore, cloud services are provided in a market dominated by few large providers (i.e., Amazon, Microsoft, and Google – see discussion in Crémer et al. 2024), suggesting the presence of a positive markup on the cost of IT assets provision via cloud services. Accordingly, purchases of cloud services are characterised by larger costs than IT proprietary assets, whose amount is likely larger in firms of greater size.

In this respect, the positive link between cloud and size may be only partially consistent with existing evidence on ICTs. Firm-level IT intensity has a positive effect on the size growth of firms, but its returns increase with firm size (Babina et al. 2024, Brynjolfsson et al. 2023). Accordingly, the diffusion of ICT technologies may generate concentration increases in many countries, in line with the positive sector-level link between intangibles and concentration found in similar settings (Bajgar et al. 2021).

Nevertheless, the use of cloud services by firms could represent a departure from this evidence, with key implications for the current trends in industry concentration. More specifically, our results suggest that the diffusion of cloud technologies among firms could mitigate concentration trends by benefiting more smaller firms in terms of size growth by boosting their digitalisation.

3 Data

In this section, we discuss the data employed in the analysis and present key summary statistics. Our analysis is based on four sources of microdata.

First, we use the 2016 and 2018 versions of the French ICT survey (*"Enquête sur les Technologies de l'Information et de la Communication (TIC)"*), which is managed by the INSEE (the French statistical office).[2] Each wave of the survey includes a rotating sample counting approximately 9000 firms from both manufacturing and non-financial market-services sectors. The sample is representative for firms with 10 or more employees and is exhaustive for those with over 500 employees.[3] We exclude firms belonging to sectors 62 ("Computer Programming, Consultancy And Related Activities") and 63 ("Information Service Activities") of the NACE classification. The possible positive effect of cloud adoption on the performance of these firms could indeed be driven by the sales of cloud services to other firms, rather than by increases in digital intensity. The survey questions focus on the utilisation of advanced digital technologies in 2015 and 2017, respectively captured by the 2016 and 2018 survey waves.[4] This dataset is characterised by a greater level of detail and representativeness when compared to other commercial surveys. Additionally, it can be merged to other sources of French firms' data thanks to the *Siren* code, a unique identifier attributed to French companies at their birth.

Part of the ICT survey is dedicated to questions on cloud use by firms. Specifically, firms are asked whether they used cloud technologies in the previous year.[5] Firms are asked the following question:

"Did your enterprise buy cloud computing services? (Excluding cloud services provided for free.)".

Cloud services are defined as follows in the survey:

"Cloud computing (or cloud) refers to computing services used over the internet to access software, computing power, storage capacity, etc. These services must have the following characteristics:

- *They are delivered by servers from service providers.*
- *They are easily scalable up or down (for example, the number of users or changes in storage capacity).*

[2]Further information about each ICT survey can be found here for 2016 and here for 2018.

[3]It is therefore challenging to exploit the panel dimension of these datasets. Less than three of thousands firms are present in both the waves of the survey, and are mostly large firms.

[4]The questions about advanced digital technologies are updated annually, although the ICT surveys run in different years may not include questions about the same technologies.

[5]Additional questions about cloud technologies are present in the 2020 and 2021 waves, relative to the years 2019 and 2020 respectively. However, in the context of our identification strategy (see Section 4), the use of these waves implies the inclusion of the COVID-19 pandemic years in the dataset. The pivotal role of digital technologies during the pandemic makes it challenging to precisely estimate the effect of cloud on performance in normal times. We chose to employ the 2016 and 2018 ICT surveys accordingly. We provide a robustness check confirming our results and estimated in the periods 2009–2019 (using ICT survey versions 2016, 2018, and 2020) and 2009–2020 (using ICT survey versions 2016, 2018, 2020, and 2021) in the Appendix (see Table A6).

- *Once installed, they can be used "on-demand," without human interaction with the provider.*

- *They are paid either by the user or based on the capacity used or services provided.*

Cloud computing may include connections via a virtual private network (VPN)."

Furthermore, the survey provides information on the different types of cloud services purchased by firms, distinguishing them into six non-exclusive categories: mail, data storage, file storage, accounting software, office software, CRM software, and computing power. We define a cloud user as a firm that purchases cloud services in at least one of the latter five categories. We discard the first category of cloud usage (i.e., mail), as it is unlikely conducive to producing organisational changes in the firm's structure and, therefore, may not capture the effects of cloud on firm performance. Our main cloud use variable thus takes the form of a dummy, indicating whether firms use cloud technologies or not. Additionally, we provide results for different categories of cloud usage. We define the dummy variables 'Cloud - Storage', 'Cloud - Software', and 'Cloud - Computing Power.' A firm is considered to use cloud for storing data ('Cloud - Storage') when it purchases cloud services for storing data or files, to use cloud for software ('Cloud - Software') when using cloud services for accounting, office, or CRM software, and to use cloud for computing power ('Cloud - Computing Power') when it purchases cloud services for borrowing external IT processing capacity.

Second, we match the ICT survey with the administrative data from French firms' balance sheets (FARE) covering the 2018-2005 period.[6] This dataset provides information on firm sales, age, employment, and exporter status, as well as physical and intangible capital.[7] Intangible capital is not available before 2009; this will limit our baseline estimation to the 2009–2018 period.[8] These variables allow us to portrait a complete picture of firms buying cloud technologies, and to control for potential links between size growth and firm characteristics otherwise conflated with cloud usage, for instance the age of firms.

Third, we employ the information on the stocks of establishments by firm from the French business register. This data is used to build a binary variable indicating if the firm is multi-plant.

Finally, we match the ICT survey with French employer-employee data (DADS) in 2005–2017.[9] This data allow us to build the firm-level share of hours worked by ICT workers

[6]Additional details about this dataset can be accessed here: https://doi.org/10.34724/CASD.42.3654.V1.

[7]Data on sales and capital are in real terms. Sales and physical capital have been deflated at the 2-digit sector level. Data on intangible capital have been deflated exploiting the deflators provided by INTANPRO-EUKLEMS (Bontadini et al. 2023).

[8]However, in Section 5.3 we discuss a series of robustness checks on the 2005–2018 period.

[9]Further information about DADS here.

hired by the firm (named ICT share hereafter). We consider ICT workers to be employees falling within the 4-digit classes 388a, 388b, 388c, 388d, 388e, 478a, 478b, 478c, 478d, and 544a of the 2003 French PCS classification.[10] These classes specifically target occupations with a significant focus on ICTs. The ICT share serves as a proxy for the intensity of digitalisation within the firm and, in a regression setting, cleans the relationship between cloud and performance from the correlation between cloud and other performance-enhancing digital technologies.

3.1 Who are cloud users?

Before investigating the relationship between cloud adoption and firm growth, we sketch out the characteristics of the sample under consideration, highlighting some general differences between cloud users and non-users. To start with, the upper block in Table 1 shows the share of cloud-adopting French firms grew of a remarkable 23 percent in only two years (from 26.5% in 2015), indicating a speedy diffusion of cloud technologies. The bottom panel of the table indicates that the share of cloud adopters increases by sales quintiles: more than a half of the firms in the top quintile adopted cloud technologies (53.2% in 2015), increasing to almost to two thirds in 2017 (64.5%). However, adoption has steadily increased across the size distribution over time.

Foreseeably, but notwithstanding the exclusion of IT services from the sample, cloud technologies are most commonly adopted by firms in the ICT sector: their adoption grew from 39.5 percent of total firms in 2015 to 57.8 percent in 2017. A similar increase – of around one third – is registered in real estate and transportation activities. Professional and scientific firms are the second highest adopter in 2017 (44,7%), although cloud adoption grew at a slower pace despite comparable shares of adopters to ICT in 2015. Low-productivity sectors such as accommodation services and administrative activities display lower levels of adoption, with limited growth over time. Unlike wholesale and retail trade services, which despite starting with low adoption rates, experienced higher diffusion of cloud technologies after two years (from 23.1% in 2015 to 29.5% in 2017). The most represented industry in the sample, manufacturing, also experienced sizeable growth in the use of cloud technologies, moving from 26.5 percent of adopters in 2015 to 32.6 percent in 2017 – a growth rate of 17 percent.

We now describe the general characteristics of cloud users versus non-users. As shown

[10] It is worth noting that, except for class 544a, this classification aligns with the techies definition used in Harrigan et al. (2021). The techies definition encompasses all occupations within the 2-digit classes 38 (executives and engineers) and 47 (Technicians) of the 2003 French PCS classification. The mentioned PCS codes cover roles such as R&D personnel in IT, computer engineers, developers, database administrators, and IT technicians. Further details and information on the PCS classification can be found here.

in Table 2, the most common use of cloud technologies in both years is to store data and files, although this particular type of cloud exhibits little growth between 2015 and 2017. This is likely due to the fact that cloud technologies for data storage were the first to be commercialised, and have reached earlier maturity. This is followed by office and CRM software applications – which increased from 66,2 percent to 76,9 percent – and lastly by ICT applications, such as the acquisition of computational power available to the firm. The latter type is the fastest growing cloud technology type among adopters, increasing of 22.64 percent in two years (from 21.2% in 2015 to 26% in 2017). Overall, Table 2 also shows that cloud-adopting firms tend to be older and remarkably larger in terms of both sales and employment. They also own a bigger stock of physical and intangible capital, employ a higher share of ICT workers (more than twice as bigger than non-adopters), and are more likely to export. Finally, cloud adopting firms are also more likely to deploy more than one productive plant.

Shares of Cloud Users

France	2015	2017
	Share	Share
All firms	.265	.326
Sales Quintile	2015	2017
	Share	Share
0-20%	.101	.132
20%-40%	.172	.18
40%-60%	.193	.261
60%-80%	.328	.418
80%	.532	.645
Industry	2015	2017
Accommodation & Food	.183	.202
Administrative	.296	.326
ICT	.396	.578
Manufacturing	.28	.341
Professional & Scientific	.388	.447
Real Estate	.292	.418
Transportation & Storage	.218	.313
Utilities & Construction	.177	.244
Wholesale & Retail	.231	.295

Table 1: Share of cloud users in 2015 and 2017: total for France, by sales quintile and by industry.

To confirm that the differences between the two types of firms in the sample are statis-

Summary Statistics

Year	2015		2017	
Cloud	0	1	0	1
Cloud – Storage	0	.873	0	.889
Cloud – Software	0	.662	0	.769
Cloud – ICT	0	.212	0	.26
Age	28.75	32.57	29.04	33.37
Sales	90311.84	335754.36	66600.45	356113.05
Employment	234.65	957.85	184.76	982.62
Physical Capital	33251.89	168873.2	19753.02	182073.1
Intangible Capital	393.66	2277.7	194.61	2231.73
ICT Share	.024	.052	.02	.052
Exporter	.441	.64	.419	.64
Multi-Plant	.436	.693	.414	.663

Table 2: Summary statistics by cloud user and year.

tically significant, we run a Probit regression to predict the likelihood of cloud adoption as a function of firm-level characteristics, including regional, industry (2 digits), and time fixed effects:

$$\begin{aligned}&\Pr(\text{Cloud}_{i,t}) = \\ &\Phi(\text{Log-Sales}_{i,t}, \text{Log-Age}_{i,t}, \text{ICT Share}_{i,t}, \text{Log-Physical Capital}_{i,t}, \\ &\text{Log-Intangible Capital}_{i,t}, \text{Exporter}_{i,t}, \text{Multi-Plant}_{i,t}, \text{2-digit Ind.}_i, \text{Region}_i, \text{Year}_t)\end{aligned} \tag{1}$$

Results of this exercise are shown in Table 3, which displays the marginal effects of firm characteristics as per Equation 1 on the probability of adopting any type of cloud technology. Most of the differences revealed by Table 2 are confirmed. Higher sales, higher share of ICT employees, higher intangible capital, exporting, and being a multi-plant firm are associated to a higher probability of adopting cloud are all associated to a greater probability to purchase cloud services. There are some notable exceptions with respect to Table 2. Interestingly, the log of physical capital is very small and not significant when controlling for the log of sales (Models 4, 5, and 7 in Table 3). This suggests that physical capital also captures a size effect. Furthermore, Models 2 to 7 indicate that after controlling for firm size, younger firms are more prone to adopt cloud technologies. A possible reason for this is that older firms had already established their own data storage facilities, designed or purchased tailored software, or set up the required hardware to acquire computing power. These are all irreversible investments, which provide negative incentives to purchase their cloud equivalent. In sum, these descriptive results show that cloud adopters tend to be remarkably different from non-adopters, hinting towards a possible self-selection of firms into the use of cloud technologies.

Probit Margins

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Log Sales	0.072***	0.073***	0.073***	0.061***	0.061***		0.055***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)		(0.003)
Log Age		-0.014**	-0.012*	-0.021***	-0.019***	-0.027***	-0.020***
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
ICT Share			0.175***		0.174***	0.164***	0.158***
			(0.038)		(0.038)	(0.038)	(0.038)
Log Physical Capital				0.004	0.004	0.018***	0.003
				(0.004)	(0.004)	(0.004)	(0.004)
Log Intangible Capital				0.008**	0.008**	0.029***	0.007**
				(0.004)	(0.004)	(0.004)	(0.004)
Exporter						0.074***	0.051***
						(0.008)	(0.008)
Multi-Plant						0.066***	0.044***
						(0.008)	(0.008)
Observations	14,594	14,594	14,594	14,594	14,594	14,594	14,594
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.164	0.164	0.165	0.165	0.166	0.166	0.170

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3: Margins based on the Probit estimation results of Equation 1.

4 Methods

In this work we aim at studying the effects of cloud purhcases on firms' sales growth. To this purpose, observing short term (e.g. one year) growth rates as the independent variable would not capture the relation at stake. Indeed, as suggested by several works (e.g. Brynjolfsson & Hitt 2003, Brynjolfsson et al. 2018, Acemoglu & Restrepo 2020, Babina et al. 2024), the effects of digital technologies diffusion may take time to materialise due to uncertainty characterising and implementation lags induced by the large and complex organisational changes associated to the adoption of ICTs. This holds true for cloud technologies as well. Indeed, as discussed in Section 2, the adoption of cloud involves a transition from investments in physical IT capital to intermediate IT costs, and therefore a complex change of the adopters' organisational structure. The impact of this change on firm performance may therefore take several years to manifest. Moreover, the ICT surveys fail to provide precise information on the first year of cloud adoption. Consequently, an estimation involving short-term growth rates may conflate the effects for firms that have been using cloud services for several years with those that have recently adopted cloud technology. In the former scenario, our observations would reflect not the cumulative impact of cloud usage but rather the impact of just one year, potentially leading to an underestimation of its effect on firm performance. In the latter scenario, the impact of cloud usage could be negligible due to the lags in the materialisation of the impact of cloud on firm performance. However, we know that the purchase of cloud services by firms before 2009 was highly improbable in the US (Bloom & Pierri 2018), probably due to the high prices associated with cloud service provision until the 2010s (Byrne et al. 2018, Coyle & Nguyen 2018). This suggests that the adoption of cloud technology by French firms, as observed in our sample for the years 2015 and 2017, very likely started after 2009.

For these reasons, we test the cloud-growth relation in the long run. Specifically, in our baseline estimations we choose as the dependent variable the largest logarithmic difference in sales allowed by our data, which corresponds to a 7-year lag.[11]. The baseline model will therefore be estimated over the 2009–2018 period. As cloud use before 2009 was very unlikely due its high price, our estimation captures the vast majority of the performance gains from cloud use for the firms included in our sample. According to this interpretation, our regression results estimate the effect of adopting cloud technologies, rather than using them, as if the dummy switched from 0 to 1 for cloud users in the period considered. In addition, the control variables are measured at the beginning of the period (i.e. 2009 and 2011) and consequently at a moment when cloud diffusion may have only exerted a negligible effect on them because its usage unlikely. This implies that the cloud-growth relationship estimated by our model is safe from bad controls bias (Angrist & Pischke 2008).[12]

Our baseline regression model reads as follows:

$$\begin{aligned}
&\text{Sales Growth}_{i,t+1,t-6} = \\
&a + \beta_1 \text{Cloud}_{i,t} + \beta_2 \text{Cloud}_{i,t} \cdot \text{Log-Sales}_{i,t-6} + \beta_3 \text{Log-Sales}_{i,t-6} + \\
&+ \beta_4 \text{Log-Age}_{i,t-6} + \beta_5 \text{ICT Share}_{i,t-6} + \\
&+ \beta_6 \text{Log-Physical Capital}_{i,t-6} + \beta_7 \text{Log-Intangible Capital}_{i,t-6} + \beta_8 \text{Exporter}_{i,t-6} + \\
&+ \beta_9 \text{Multi-Plant}_{i,t-6} + \beta_I \text{2-digit Ind.}_i + \beta_R \text{Region}_i + \beta_Y \text{Year}_t + \epsilon_{i,t}
\end{aligned} \tag{2}$$

where Sales Growth$_{i,t+1,t-6}$ is the logarithmic difference between sales in $t+1$ and $t-6$,

[11]The intangible capital variable is unavailable before 2009 and the first year in which information on cloud purchases by firms is available in the ICT surveys is 2015. We also test the relation with a 5-years difference (in the 2010–2018 sample) and, dropping the intangible capital variable, between 2005 and 2018 (see the discussion in Section 5.3)

[12]Our model is very similar to the one employed in Babina et al. (2024), wherein the long run effect of changes in AI investments on growth rates of size is tested by controlling for firm characteristics at the beginning of the period.

$\text{Cloud}_{i,t}$ is the cloud dummy, $\text{Log-Sales}_{i,t-6}$ are the lagged sales of firms in logarithmic scale, $\text{Log-Age}_{i,t-6}$ is the logarithm of the lagged age of firms, ICT $\text{Share}_{i,t-6}$ is the lagged share of hours worked by ICT personnel in the firm, Log-Physical $\text{Capital}_{i,t-6}$ is the logarithm of lagged physical capital, Log-Intangible $\text{Capital}_{i,t-6}$ is the logarithm of lagged intangible capital, $\text{Exporter}_{i,t-6}$ is a dummy equal to 1 if a firm exported in $t-6$, $\text{Multi-Plant}_{i,t-6}$ is a dummy equal to 1 if a firm had more than one establishment in $t-6$, and 2-digit Ind._i, Region_i and Year_i are 2-digit industry, regional and year dummies.

The coefficient on $Cloud_{i,t}$ captures the average increase in sales due to cloud use, conditional on the aforementioned controls. Furthermore, the interaction term between sales and cloud enables us to account for potential (dis)economies of scale in cloud usage, as thoroughly discussed in Section 2. Due to the inclusion of the lagged value of sales in logarithmic scale, Equation 2 can be interpreted as a Beta-Convergence model.

Finally, we also add a series of additional covariates defining a complete characterisation of firms. These variables serve as controls, allowing us to account for various crucial firm characteristics that could potentially confound the relationship between sales growth and cloud adoption. The ICT share variable addresses the self-selection bias of more digitalised firms into cloud usage. Cloud technology is known to complement several digital technologies (McElheran et al. 2023, Calvino & Fontanelli 2023*b*), which, in turn, may inherently impact firms' growth rates. Additionally, larger firms are more likely to adopt digital technologies (Zolas et al. 2020, Calvino & Fontanelli 2023*a*). Hence, the inclusion of sales as a control addresses both the self-selection of larger firms into cloud use and the potential utilisation of other digital technologies. The inclusion of age among the controls accounts for the self-selection of firms with new managerial ICT capabilities into cloud usage (Bloom & Pierri 2018). The age-capabilities link may also influence the odds of using other digital technologies, such as AI (Calvino & Fontanelli 2023*a*), and its presence therefore mitigates the potential bias introduced by omitted variables. The inclusion of firm age as control also helps clear the size-cloud interaction. The presence of a variable controlling for firm capital addresses the self-selection of firms into cloud use: first, intangible capital may correlate with the availability of other digital technologies and complementary assets, such as proprietary data and software. Second, physical capital affects the feasibility of using cloud technologies, with firms possessing lighter capital structures potentially having higher adoption potential. Third, a large availability of intangible capital may positively affect the growth of firms, because associated to other digital technologies (Corrado et al. 2021). Dummies identifying firms that conduct export activities, and that hold multiple plants are included to control for the exploitation of multiple markets, addressing the self-selection of firms with larger growth potential into cloud usage. A set of dummies capturing the average characteristics of 2-digit

NACE sectors, French regions, and years is incorporated.

4.1 Identification strategy

We first estimate Equation 2 via Ordinary Least Squares (OLS). Notwithstanding the presence of several controls and fixed effects, the estimation could still exhibit biases owing to endogeneity in the relationship between cloud and size growth, because the adoption of the former may be associated with unobserved characteristics of the firms, such as their managerial and productive capabilities. In order to address the remaining sources of endogeneity linked to the self-selection of firms into the adoption of cloud technologies, we exploit a source of spatial exogenous variation associated to the costs and quality of IT investments. We build on evidence by Andersen et al. (2012) that IT investments are slowed down by the incidence of a natural phenomenon: lightning strikes. The argument proposed by Andersen is based on the correlation between lightning strikes density and productivity across US states which emerged in the 1990s, years in which ICTs started to diffuse more widely. By causing energy spikes and dips, lightning strikes increase the cost of digital infrastructures and technologies, slowing down their diffusion. The incidence of lighting strikes also reduces the quality of broadband connections; it has been shown that broadband network failures are four times more likely during thunderstorms (Schulman & Spring 2011). However, in order to adopt cloud technologies, firms need to have access to reliable, fast and state-of-art internet connection (Nicoletti et al. 2020, Garrison et al. 2015, Ohnemus & Niebel 2016), which is fostered by the presence of physical infrastructures providing high-quality broadband connections. This, in turn, is more likely to be available in areas with lower density of lightning strikes per capita. As a matter of fact, a measure of lightning strikes density per capita reflects the trade-off faced by internet providers who will have to balance the costs of expanding the broadband network (influenced by the disruption caused by lightning-related spikes and dips) and the potential benefits that can be harvested by expanding their services, given by the number of potential customers in each geographical area (Guriev et al. 2021, Caldarola et al. 2023).

We report in Table 4 the estimated margins of a Probit model employing the presence of fast broadband as dependent variable and the log of lighting strike density as the dependent variable. Fast broadband is a dummy variable taking value 1 when firms broadband connection is faster than 100 mbit per second. We source this information from the ICT surveys described at the beginning of Section 3. Information on lightning strike density is obtained from the World Wide Lightning Location Network (WWLLN) Global Lightning Climatology and Timeseries (Kaplan 2023). The raw WWLLN data is a grid of 5-arcminute cells, each containing information on the count of daily lightning strikes per square kilometer. Data

Fast broadband and lighting strike density		
	Model 1	Model 2
Log Lighting Strike Density	-0.006***	-0.004***
	(0.001)	(0.001)
Log Sales		0.013***
		(0.002)
Log Age		-0.003
		(0.002)
ICT Share		0.073**
		(0.029)
Log Physical Capital		-0.000
		(0.003)
Log Intangible Capital		-0.001
		(0.003)
Exporter		0.021***
		(0.004)
Multi-Plant		0.010**
		(0.004)
Observations	14,294	14,294
Ind. FE	Yes	Yes
Year FE	Yes	Yes
Reg. Fe	Yes	Yes
Pseudo R2	0.0487	0.103

Table 4: Models 1 and 2 are probit margins estimation using the use of fast broadband by the firm as a dependent variable.

collection occurs daily and spans from 2008 to 2020. Building on evidence that the incidence of lightning strikes is a stationary phenomenon (Andersen et al. 2012), we are interested in constructing a measure that captures the geographical exposure of geographical areas to this phenomenon (in our case, the French municipality where firms are located).[13] We therefore calculate the average lightning strike density for each French municipality, based on the density values contained in the cells that fall within each municipality over the period 2008 – 2017.[14] The resulting metric, representing daily lightning strikes per square kilometer in each municipality, is further transformed into daily lightning strikes per inhabitant. This conversion involves multiplying the density by the municipality's surface area and dividing it by its population.[15]

[13]French municipalities, or communes, are the smallest administrative subdivision in France, acting as local authorities. There are 34,826 communes in the country.

[14]In the case of cells that fall over a border between two or more communes, the cropped cells weight in each commune based on the percentage of the cell falling within each of them.

[15]We source the population data at the municipality level from French official statistical sources at this link.

As shown in Table 4, lighting strike density is negatively associated to the use of fast broadband connections by firms, in line with our discussion above. The relation is strongly significant, even when additional controls are included. Among these, we also find that the direct (ICT share) and indirect (sales) proxies of digitalisation have positive and significant association with fast broadband, suggesting that the lighting strike density is directly correlated with the presence of fast broadband.

Following the same rationale, we employ per-capita lightning strikes to identify cloud adoption in Equation 2 in an Endogenous Treatment regression framework (referred to as ET hereafter Heckman 1976, 1978, Maddala 1983), a latent variable approach widely used in research (e.g., Shaver 1998, King & Tucci 2002, Campa & Kedia 2002) and closely related to conventional instrumental variable (IV) models such as two-stage least squares (2SLS) (Vella & Verbeek 1999). This model allows to address the issue of self-selection among firms engaging into treatment (Hamilton & Nickerson 2003, Clougherty et al. 2016) – cloud use in our case – by simultaneously estimating a selection and an outcome model via Maximum Likelihood Estimation (MLE). Furthermore, the ET method offers the advantage of employing a Probit model for the selection equation, which does not generate predicted values outside the unity range of the probability space – unlike Linear Probability Models. This is particularly relevant in our case, where the endogenous variable – cloud adoption – is dichotomous.

In the context of the ET framework, Equation 2 reads as follows:

$$\begin{aligned}
&\text{Sales Growth Rate}_{i,t+1,t-6} = \alpha + \beta_1 \text{Cloud}_{i,t} + \beta_2 \text{Cloud}_{i,t} \cdot \text{Log-Sales}_{i,t-6} + \beta_{\mathbf{X}} \mathbf{X}_{i,t-6} + \epsilon_{i,t} \\
&\text{Cloud}_{i,t} = \begin{cases} 1, & \text{if } \beta_Z \text{Log-Lighting Density}_i + \beta_{\mathbf{X}} \mathbf{X}_{i,t-6} + \omega_{i,t} > 0 \\ 0, & \text{otherwise} \end{cases}
\end{aligned} \tag{3}$$

where $\text{Cloud}_{i,t}$ is the endogenous dummy variable for the use of cloud, $\mathbf{X}_{i,2011}$ is a vector of controls including the same variables of Equation 2 and the variable Log-Lighting Density_i, which is excluded from the outcome equation. The estimation of the ET model employs the Full Information Maximum Likelihood (FIML) method, concurrently estimating the selection equation (using the dummy variable for cloud use as the dependent variable) and the outcome equation (i.e., the sales growth rate regression).[16] The ET model produces estimates robust to the presence of specification errors when an additional variable is incorporated into the selection equation, but omitted from the outcome equation. This variable must adhere to two conditions (Puhani 2000), similarly to the standard IV conditions of 2SLS: it must strongly predict the endogenous dummy variable (i.e., exhibit relevance) and must be exogenous (i.e.,

[16]This process assumes the joint normality of errors (ϵ_i, ω_i)

satisfy the exclusion restriction) in the presence of other controls.

The exclusion restriction of lighting density		
	Model 1	Model 2
Log Lighting Density	0.005	-0.004
	(0.003)	(0.003)
Log Sales		-0.053***
		(0.004)
Log Age		-0.108***
		(0.005)
ICT Hours Share		0.381***
		(0.048)
Log Physical Capital		0.017***
		(0.006)
Log Intangible Capital		-0.010
		(0.006)
Exporter		0.043***
		(0.011)
Multi-Plant		0.014
		(0.011)
Observations	14,605	14,605
R-squared	0.036	0.103
Ind. FE	Yes	Yes
Year FE	Yes	Yes
Reg. Fe	Yes	Yes
Adj R2	0.0314	0.0983

Table 5: Checks on the exclusion restriction condition of the lighting strike density. Models 1 and 2 are OLS estimation where the sales growth rate is the dependent variable.

We provide evidence in favour of the exclusion restriction hypothesis of lighting strikes density on Table 5. We report two regressions employing the long run sales growth rate as dependent variable and the log of lighting density as the dependent variable. Independently from the presence of the controls of Equation 2, the relation between firm growth and lighting density is not significant. This suggests that the spatial variation in this natural phenomenon does not affect directly the location choice of high growth firms, as their distribution is independent of the exposure of their location to lightnings. While the validity of the exclusion restriction cannot be tested against an alternative hypothesis, these results support the idea that the lighting strike density at the municipality level is exogenous, and that it affects sales growth only via cloud adoption, which as discussed, relies heavily on the availability of a fast and reliable broadband connection.

5 Results

In this section we discuss our estimation results. In Section 5.1, we discuss the estimation of of the econometric models described in Section 4. Next, in Section 5.2 we explore the effect of different types of cloud technologies (i.e. cloud for storage, software use and computational power). Finally, in Section 5.3 we discuss a battery of robustness checks.

5.1 Cloud adoption and firm growth

Sales growth (long differences): OLS

	Model 1	Model 2	Model 3	Model 4	Model 5
Cloud	0.064***	0.155***	0.140***	0.418***	0.389***
	(0.014)	(0.012)	(0.012)	(0.053)	(0.049)
Log Sales		-0.068***	-0.061***	-0.059***	-0.053***
		(0.003)	(0.003)	(0.003)	(0.003)
Cloud*Log Sales				-0.027***	-0.025***
				(0.005)	(0.004)
Log Age			-0.105***		-0.106***
			(0.006)		(0.006)
ICT Share			0.357***		0.345**
			(0.110)		(0.111)
Log Physical Capital			0.016*		0.016**
			(0.008)		(0.007)
Log Intangible Capital			-0.010		-0.009
			(0.007)		(0.007)
Exporter			0.036***		0.034***
			(0.008)		(0.008)
Multi-Plant			0.009		0.009
			(0.008)		(0.009)
Observations	14,605	14,605	14,605	14,605	14,605
R-squared	0.038	0.084	0.114	0.086	0.115
Ind. FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Reg. Fe	Yes	Yes	Yes	Yes	Yes
Adj R2	0.0337	0.0790	0.109	0.0809	0.110

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6: Results of estimation Equation 2.

We discuss the association between adoption of cloud technologies and growth of French firms in 2015 and 2017, using the long differences strategy set out in Section 4. It is worth recalling that, in our baseline model, we consider the growth rate in terms of the (log differences of) sales of the firm between 6 years before the survey period (2015 or 2017) and one year after – an approach that we refer to as long differences (Acemoglu & Restrepo 2020). The main explanatory variable identifies firms that use cloud technology on the survey year. All covariates are measured six years before the one of the survey. The results of the estimation are summarised in Table 6.

Model 1 of the table shows that there is a positive and statistically significant relationship between the use of cloud technologies and the long run growth of sales. Adding the log of sales (Model 2) leads to a notable increase in the magnitude of the coefficient on cloud. This may be due to the higher frequency of cloud use among larger firms (see Section 3.1), coexisting with a smaller impact of cloud use on their performance. This hints to the fact that possible effects of cloud on firm performance may be mediated by their size. Moreover, this proxy for firm size enters with a negative sign, consistently across specifications (Models 2 to 5), and suggesting the presence of decreasing marginal returns on growth based on firm size. This result is robust to the addition of relevant covariates (Model 3). Analogously, age has a negative relation with firm performance. The ICT share is positively related with firm performance in the long run, in line with existing evidence (Acemoglu et al. 2022, Brynjolfsson et al. 2023). Physical capital is positive and significant, whereas the performance-intangible capital link is not significant. The latter relation could be due to the presence of ICT share as a control, that is highly correlated with the presence of intangibles. Finally, exporting firms are characterised by better long run performance, as they are able to leverage a larger number of markets.

We are particularly interested in understanding whether the adoption of cloud technologies affects differently smaller and larger firms. This has a key policy relevance, because the use of cloud technologies could mitigate the increases in concentration related to the diffusion of ICTs and intangibles (Brynjolfsson et al. 2023, Babina et al. 2024, Bajgar et al. 2021) due to the joint action of scale without mass and large fixed costs in IT investments. To test this hypothesis, we focus on the interaction term between cloud adoption and log sales (Models 4 and 5 in Table 6). In both specifications, the interaction term takes a negative sign, confirming that larger firms benefit less – in terms of sales growth – than smaller firms. Thanks to the diffusion of cloud technologies, smaller firms have access to affordable means to increase the scale of their operations by digitalising production processes. They can externalise digital storage space, software tools and computing power, thus avoiding irreversible investments into the physical facilities (such as servers or computing clusters) or specialised employees (engineers specialised in ICT, such as computer networks engineers) required to this aim.

As shown in Section 3.1, cloud adopting firms are systematically different from non adopt-

Sales growth (long differences): Endogenous Treatment				
	Model 1		Model 2	
	Performance	Adoption	Performance	Adoption
Cloud	0.122***		0.435***	
	(0.022)		(0.045)	
Log Sales	-0.059***	0.193***	-0.055***	0.192***
	(0.003)	(0.012)	(0.004)	(0.013)
Cloud*Log Sales			-0.026***	
			(0.004)	
Log Age	-0.105***	-0.060***	-0.105***	-0.060***
	(0.006)	(0.013)	(0.006)	(0.014)
ICT Share	0.360***	0.506**	0.338***	0.506**
	(0.110)	(0.227)	(0.107)	(0.227)
Log Physical Capital	0.016**	0.028	0.016**	0.027
	(0.008)	(0.018)	(0.007)	(0.018)
Log Intangible Capital	-0.010	-0.014	-0.009	-0.013
	(0.007)	(0.016)	(0.006)	(0.016)
Exporter	0.037***	0.180***	0.033***	0.179***
	(0.008)	(0.028)	(0.008)	(0.028)
Multi-Plant	0.010	0.140***	0.007	0.140***
	(0.008)	(0.031)	(0.009)	(0.031)
Log Lighting Strike Density		-0.053***		-0.054***
		(0.011)		(0.011)
Observations	14,605	14,605	14,605	14,605
Ind. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Reg. Fe	Yes	Yes	Yes	Yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7: Results of estimation Equation 3.

ing ones, revealing the possible presence of self-selection into the use of this technology. In order to address this concern, and to offer a causal interpretation of the effect of cloud technologies on firm growth, we proceed by illustrating the results of estimating the Endogenous Treatment model described by Equation 3. This empirical approach has been designed following the identification strategy illustrated in Section 4.1, based on the spatial exogenous variation in the density of lightning strikes to address the self-selection of firms into the adoption of cloud technologies. In this way, we are able to estimate the causal effect of the adoption of cloud on sales growth. The ATE corresponds to the cloud coefficient, absent interaction with size.

The results of the ET estimation are reported in Table 7. We start by focusing on Model 1, which shows two columns: "Adoption" for the selection equation of the ET (i.e. the

Endogenous Treatment equation in the second row of Equation 3), and "Performance" which displays the results of the outcome equation (first row of Equation 3). We start from the adoption equation in Model 1. As expected, the coefficient on our instrument based on the average lightning strike density per capita between 2008 and 2017 shows a negative sign and strong statistical significance, indicating that firms located in areas with high incidence of lightnings per inhabitant are less likely to adopt cloud technologies.

The Performance column in Model 1 shows the results of the outcome equation in the ET model. The ATE of cloud on firm growth turns out to be positive and statistically significant, and of a magnitude very close to the one of the OLS coefficient in Table 6, Model 3. The results for Model 2 in Table 7 include the interaction term between firm size and cloud adoption, and are very much in line with the OLS model 5 in Table 6, as they also indicate that smaller firms reap relatively more benefits in terms of sales growth after adopting cloud technologies, when compared to larger ones.

The evidence discussed in this section confirms the existence of a scale without mass dynamic concerning the diffusion of cloud technologies among French firms (see also Jin & McElheran 2019, Duso & Schiersch 2022, DeStefano et al. 2023). Nevertheless, we show that the returns to cloud become smaller as size increases. In light of the existing evidence on the higher returns gained by larger firms adopting digital technologies (Brynjolfsson et al. 2023, Babina et al. 2024), our evidence suggests that the intrinsic characteristics of cloud technologies make them different from other ICTs, and that their diffusion among firms may help in levelling the playing field by helping smaller firms to compete by adopting advanced and complementary digital technologies, such as AI.

5.2 Heterogeneous effects by cloud type

In this section we explore the heterogeneity of the effect of cloud on the performance of firms. More specifically, we delve into the impact that different types of cloud technologies produce on the performance of firms. Different types of cloud technologies enable different complementary ICTs and operations in the firm. They are therefore likely to affect the growth of firms' sales with different intensity. We test this conjecture by estimating Equations 2 and 3 for storage, software, and ICT cloud technologies separately. To recall, the first one includes data storage services; the second one groups together office and customer relations management software services; and the third one refers to services through which the firm can acquire computing power.

Results of the ET estimation for the three different classes of cloud services are shown in Table 8, The respective OLS results are reported in the Appendix (Table A1). Overall, the findings discussed in Section 5.1 are confirmed by the results in Table 8, showing that cloud is found to have a positive effect decreasing with firm size. Furthermore, models 1, 3, and 5 indicate that the strongest effect on firms' sales growth is given by the purchase of cloud services for storing data and files, followed by the ones for using software and borrowing external computational power. However, as shown by Models 2, 4, and 6 in Table 8, this order is reverted after adding the interaction term between size and cloud by type: cloud services for software and computational power increase remarkably their size effect with respect to storage technologies. Conversely, the point estimate of the (negative) interaction term increases following the same order. This indicates that the returns to cloud fall more rapidly for larger firms when the sophistication and cost of the investment that would be needed to implement in-house the substitute digital operation increases.[17] In a policy perspective, this suggests that the diffusion of cloud technologies should focus on advanced cloud services to mitigate the increasing trends in concentration.

[17]The same pattern is confirmed by the results shown in Table A1, which displays the OLS coefficient estimates of the impact of the three cloud types on firm growth.

Sales growth (long differences) by cloud type: Endogenous Treatment Model

Cloud type	Cloud for Storage				Cloud for Software				Cloud for Computational Power			
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Performance	Adoption	Performance	Adoption	Performance	Adoption	Performance	Adoption	Performance	Adoption	Performance	Adoption
Cloud	0.111***		0.458***		0.050*		0.499***		0.065***		0.688***	
	(0.024)		(0.044)		(0.027)		(0.044)		(0.024)		(0.115)	
Log Sales	-0.058***	0.174***	-0.054***	0.174***	-0.054***	0.177***	-0.051***	0.177***	-0.053***	0.156***	-0.052***	0.155***
	(0.003)	(0.010)	(0.004)	(0.011)	(0.004)	(0.011)	(0.004)	(0.012)	(0.003)	(0.012)	(0.003)	(0.011)
Cloud*Log Sales			-0.028***				-0.035***				-0.049***	
			(0.004)				(0.005)				(0.010)	
Log Age	-0.105***	-0.065***	-0.105***	-0.065***	-0.107***	-0.054***	-0.106***	-0.053***	-0.107***	-0.046**	-0.106***	-0.045**
	(0.006)	(0.014)	(0.006)	(0.014)	(0.007)	(0.010)	(0.006)	(0.010)	(0.007)	(0.019)	(0.006)	(0.019)
ICT Share	0.365***	0.442*	0.341***	0.442*	0.373***	0.542**	0.341***	0.542**	0.376***	0.513**	0.352***	0.511**
	(0.109)	(0.261)	(0.106)	(0.262)	(0.113)	(0.243)	(0.109)	(0.243)	(0.115)	(0.201)	(0.115)	(0.202)
Log Physical Capital	0.016**	0.031**	0.016**	0.030**	0.017**	0.012	0.017**	0.011	0.017**	0.016	0.018**	0.014
	(0.008)	(0.015)	(0.007)	(0.015)	(0.008)	(0.016)	(0.007)	(0.017)	(0.008)	(0.020)	(0.008)	(0.019)
Log Intangible Capital	-0.010	-0.017	-0.009	-0.016	-0.010	-0.005	-0.009	-0.004	-0.010	-0.014	-0.010	-0.013
	(0.007)	(0.014)	(0.006)	(0.014)	(0.007)	(0.010)	(0.007)	(0.011)	(0.007)	(0.020)	(0.007)	(0.020)
Exporter	0.038***	0.159***	0.034***	0.158***	0.041***	0.206***	0.035***	0.205***	0.042***	0.120***	0.040***	0.119***
	(0.007)	(0.029)	(0.007)	(0.029)	(0.008)	(0.031)	(0.008)	(0.032)	(0.007)	(0.045)	(0.007)	(0.045)
Multi-Plant	0.011	0.136***	0.008	0.136***	0.013	0.165***	0.009	0.164***	0.014*	0.143***	0.011	0.144***
	(0.008)	(0.024)	(0.009)	(0.023)	(0.008)	(0.018)	(0.009)	(0.018)	(0.009)	(0.032)	(0.010)	(0.032)
Log Lighting Strike Density		-0.052***		-0.053***		-0.051***		-0.052***		-0.050***		-0.052***
		(0.012)		(0.012)		(0.011)		(0.011)		(0.010)		(0.010)
Observations	14,605	14,605	14,605	14,605	14,605	14,605	14,605	14,605	14,605	14,605	14,605	14,605
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8: Results of estimation Equation 3, for different cloud types

5.3 Robustness checks

We conduct a battery of robustness checks, in order to further support the results summarised in the previous subsection. For the sake of conciseness, the results of this final exercise are shown in the Appendix.

First, we adopt an alternative measure of firm size based on the size of firms' employment rather than sales. We replace the new firm size measure as i) both the outcome and dependent variables (Table A2) or ii) the dependent variable only (Table A3) in both equations 2 and 3, and re-estimate both long differences models using OLS and ET. As shown in Tables A2 and A3, the results are perfectly consistent with the patterns observed in Tables 6 and 7: firms with more employees grow less rapidly after adopting cloud technologies when compared to firms with fewer employees.[18] The latter are likely to benefit more of the adoption of cloud technologies and will be able to hire more employees relative to their size. This result is particularly interesting to understand the mitigating effect of cloud technologies on concentration trends: not only these apply to firm's total production, but also to their ability to hire new employees.

The second robustness check consists of changing the time interval initially chosen to set up the long-difference approach outlined in Equations 2 and 3. First, we repeat the estimation of the OLS and ET long-difference models computing growth between $t+1$ and $t-5$, instead of $t-6$. Second, we increase the period of the long difference by computing it between $t+1$ and $t-10$. Table A4 shows the results of this exercise; for both OLS and ET, we find substantial consistency with the long difference approach based on 7-years growth intervals.

As a third exercise, we follow the long differences approach by (Acemoglu & Restrepo 2020). This approach allows to take longest possible time interval given the data, which is now constructed by calculating firm growth between the first year available in the data for each firm at each time period (t_0) and the last one (t_1+1):

$$\begin{aligned}
&\text{Sales Growth}_{i,t_1+1,t_0} = \\
&a + \beta_1\text{Cloud}_i + \beta_2\text{Log-Sales}_{i,t_0} + \beta_3\text{Log-Age}_{i,t_0} + \beta_4\text{ICT Share}_{i,t_0} + \\
&+ \beta_5\text{Log-Physical Capital}_{i,t_0} + \beta_6\text{Log-Intangible Capital}_{i,t_0} + \beta_7\text{Exporter}_{i,t_0} + \\
&+ \beta_8\text{Multi-Plant}_{i,t_0} + \beta_I\text{2-digit Ind.}_i + \beta_R\text{Region}_i + \beta_Y\text{Year}_i
\end{aligned} \tag{4}$$

where Cloud_i indicates whether cloud was adopted between t_1+1 and t_0 (i.e. either in 2015

[18] Our results are broadly in line with results from studies estimating a positive relation between digital investments and employment dynamics (e.g. Domini et al. 2021, Bisio et al. 2023, Ughi & Mina 2023)

or in 2017). We test the regression using 2005 and 2009 as the base year. Results are shown in Table A5 and prove to be robust to the new specification, for both base years.

Finally, we conduct an additional check by adding two additional waves of the ICT survey, collected in 2019 and 2020 (Tables A6). Despite the significant disruption brought by the global COVID-19 pandemic that started in early 2020, once more the estimation results remain perfectly consistent with the original findings, where cloud affects positively the growth of firms, but more so for smaller firms.

5.4 Mechanisms

In this subsection we discuss the mechanism driving the findings discussed above. In particular, we study whether firms using cloud are associated to higher long-run increases in digital intensity, enabled by cloud adoption, and if this association depends on initial firm size.

We estimate the baseline equation 2 using the long run growth of the digital intensity as the dependent variable:

$$\begin{aligned}
&\text{ICT Share Growth}_{i,t+1,t-6} = \\
&\alpha + \beta_1 \text{Cloud}_{i,t} + \beta_2 \text{Cloud}_{i,t} \cdot \text{Log Sales}_{i,t-6} + \\
&+ \beta_X \text{Controls}_{i,t-6} + \epsilon_{i,t}
\end{aligned} \tag{5}$$

Where the share of ICT hours worked is our measure of digital intensity and included controls are the same discussed in Section 4. As in Equation 3, we instrument the use of cloud with the logarithm of lighting strikes per capita.

We report the estimates for Equation 5 in Table 5.4. The relation between the use of cloud technologies and the long-run growth rates of the share of hours worked by ICT employees is positive (Model 1), suggesting that the purchase of cloud services helps firms to increase their digital intensity. We introduce the interaction between initial size and cloud in Model 2. The coefficient on the interaction has term is negative and significant, whereas the one on cloud remains positive and significant. This result reveals that cloud purchases are associated to long-run increases in digital intensity, which are larger for smaller firms. When estimating the endogenous treatment model (Model 3 and 4), cloud turns out to have a positive effect on the growth rate of firm-level digital intensity, with larger firms being less affected.

These results highlight that the use of cloud enables the digitalisation of firms, as it increases the share of hours worked by ICT workers as compared to non-ICT ones. Indeed, the use of cloud may shift the large fixed costs incurred by firms investing in IT assets to intermediate costs, lowering barriers to digitalisation. However, we also find that smaller firms benefit more from cloud services by increasing their digital intensity to higher extents.

Share of ICT hours worked growth (long differences)						
	Model 1	Model 2	Model 3		Model 4	
Cloud	0.006***	0.026**	0.006***		0.028**	
	(0.002)	(0.011)	(0.002)		(0.011)	
Log Sales	-0.000	0.000	-0.000	0.192***	0.000	0.192***
	(0.001)	(0.001)	(0.001)	(0.023)	(0.001)	(0.023)
Cloud * Log Sales		-0.002**			-0.002**	
		(0.001)			(0.001)	
Log Age	-0.002*	-0.002*	-0.002*	-0.062***	-0.002*	-0.062***
	(0.001)	(0.001)	(0.001)	(0.018)	(0.001)	(0.018)
Share of ICT hours	-0.259***	-0.260***	-0.259***	0.500**	-0.260***	0.500**
	(0.033)	(0.033)	(0.033)	(0.206)	(0.033)	(0.206)
Log Physical Capital	0.001	0.001	0.001	0.025	0.001	0.025
	(0.001)	(0.001)	(0.001)	(0.018)	(0.001)	(0.018)
Log Intangible Capital	-0.002	-0.002	-0.002	-0.011	-0.002	-0.011
	(0.001)	(0.001)	(0.001)	(0.025)	(0.001)	(0.025)
Exporter	0.002	0.001	0.002	0.180***	0.001	0.180***
	(0.001)	(0.001)	(0.001)	(0.067)	(0.001)	(0.067)
Multi-Plant	0.002	0.002	0.002	0.142***	0.002	0.142***
	(0.001)	(0.001)	(0.001)	(0.027)	(0.001)	(0.027)
Log Lighting Strike Density				-0.053***		-0.053***
				(0.010)		(0.010)
Observations	14,591	14,591	14,591	14,591	14,591	14,591
Adj R2	0.143	0.144				
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Fe	Yes	Yes	Yes	Yes	Yes	Yes
ρ			-0.00140	-0.00140	-0.0124	-0.0124

Table 9: Estimation results of Equation 5.

This is particularly relevant since smaller firms are often less digitalised (Zolas et al. 2020). Accordingly, in light of the heterogeneous relation between size and cloud discussed in Section 5.1, cloud services may help smaller firms boost their sales by supporting their digitalisation, thus leveling the playing field with larger competitors.

6 Cloud and industry concentration

In Section 5, we demonstrated that the adoption of cloud services positively impacts firms' long-term sales growth rate, with smaller firms growing more by leveraging cloud technologies to narrow their digital gap. While this finding may seem to contradict those studies that hint towards a positive link between ICT and industry concentration (Bajgar et al. 2021, Babina et al. 2024, Bryjolfsson et al. 2023), the widespread adoption of cloud technologies could counteract the increasing concentration trends observed in several economies (Bajgar et al. 2019).

Accordingly, we aggregate our data and estimate the following Equation (Bessen 2020, Brynjolfsson et al. 2023):

$$\begin{aligned}&\text{Concentration Growth}_{s,t+1,t-6} = \\ &\alpha + \beta_1 \text{Cloud Share}_{s,t} + \beta_2 \text{Controls}_{s,t-6} + \text{2-digit Ind.}_s + \text{Year}_t\end{aligned} \tag{6}$$

Where s are 2-digit sectors and t is either 2015 or 2017, Concentration Growth$_{s,t+1,t-6}$ is the percentage change in the HHI (Herfindahl-Hirschman Index) between $t-6$ and $t+1$, Cloud Share$_{s,t}$ is the share of firms in each industry that purchased cloud services at or before time t, Controls$_{i,t-6}$ include the logarithm of the share of ICT workers in each industry, the sum of the firm-level sales and the sum of employees of firms active in sector s, 2-digit Ind.$_s$ and Year$_t$ are industry and year fixed effects.[19]

Table 10 reports the estimation results of Equation 6. The baseline models (Models 1-2) reveal a negative relationship between the growth of concentration and the share of firms adopting cloud services. This relationship remains consistent even after the inclusion of industry and year fixed effects. The robustness of these results is confirmed across different specifications: when observations are weighted by industry sales share (Model 3), and when the 2-digit HHI is calculated as a weighted average of the HHI at the 4-digit level (Model 4). Furthermore, when estimating the share of cloud adopters across different size thresholds (Models 5, 6, 7), the results remain positive and significant for firms with less than 250 employees. However, the relationship weakens as the size threshold increases, and its significance wanes for firms with more than 250 employees. This result aligns with the discussion in Section 5, suggesting that the adoption of cloud technologies by small firms is negatively related with concentration. This result also confirms that larger firms reap fewer competitive advantages from cloud adoption, as concentration among larger firms does not change significantly after they adopt the technology.

7 Conclusions

In accordance with the extant literature on the impact of cloud adoption on firm growth, our paper has shown that cloud technologies have a positive effect on the sales growth of

[19]We observe industries at the 2-digit level as the low number of firms in the sample does not allow us to measure the share of firms purchasing cloud at lower levels of aggregation. We excluded sectors 12 (tobacco products) and 19 (coke and refined petroleum products).

	Baseline		Weighted	4-digit HHI
	Model 1	Model 2	Model 3	Model 4
Cloud Share	-0.760**	-0.480***	-0.453**	-0.378***
	(0.314)	(0.170)	(0.214)	(0.097)
Observations	118	118	118	118
Ind. FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Adj R2	0.0764	0.629	0.669	0.744

	Cloud Share			
	<50	<100	<250	250+
	Model 5	Model 6	Model 7	Model 8
Cloud Share	-0.571**	-0.496**	-0.446**	-0.008
	(0.274)	(0.222)	(0.189)	(0.270)
Observations	118	118	118	118
Ind. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Adj R2	0.638	0.632	0.629	0.618

Table 10: Estimation result of Equation 6. Model 1-2 use the HH index computed at the 2-digit level, Model 3 weights observations by the market share of sectors, Model 4 estimates the 2-digit HH as the weighted average of the HH at the 4-digit level, Model 5-8 estimate the share of firms adopting cloud in firms below 50, 100 and 250 employees, or in firms with more than 250 employees.

the average firm. Consequently, their diffusion and adoption should be encouraged, and even more so if we consider the distinction between small and large firms. Indeed, our results expand the extant literature by showing that small firms benefit more in terms of size growth than larger ones from adopting cloud services. Furthermore, not all cloud technologies work in the same way. Returns to the use of cloud technologies tend to be larger for smaller firms when the cloud applications involved become more advanced, and substitute investments related to higher fixed costs.

We show that digital gaps between firms of different size could explain the cloud-growth of size relation. The use of cloud helps firms to go digital, and smaller ones benefit from cloud to higher extents.

Finally, in line with emerging evidence (see for instance Lu et al. 2024), we show that the higher benefits reaped by smaller firms counteracts the rising trends in industry concentration. Our findings in fact indicate that industries with a higher share of cloud-using firms tend to be less concentrated.

Investigating the firm-level relation between cloud and performance as mediated by size holds key policy relevance in the current economic context, characterised by increasing trends in industry concentration (see e.g., Gutiérrez & Philippon 2017, Bajgar et al. 2019, Grullon et al. 2019, Autor et al. 2020). In this regard, existing evidence suggests that digitalisation may positively affect concentration by favouring more firms which are larger. Intangibles assets and concentration are positively linked at the industry level (Bajgar et al. 2021). Also, several measures related to the IT dimension of firms have been found to generate higher returns for larger firms (Bessen 2020, Brynjolfsson et al. 2023, Babina et al. 2024, Lashkari et al. 2024).

The relationship between IT and performance, as mediated by firm size, can therefore be recognised as one of the causes of the concentration increases observed in several countries. However, the use of cloud by firms may be the exception to the rule. Contrary to the evidence from other ICTs and as suggested by our empirical findings, the diffusion of cloud technologies among firms has the potential to mitigate the worrying trends of industrial concentration by enhancing the digitalisation and growth of smaller firms more than larger ones, ensuring a more inclusive digital transition. The adoption of cloud services – in particular of more sophisticated ones – should be encouraged in order to support the digitalisation and growth of smaller firms, and to mitigate the ever-growing concentration within industries where larger (and fewer) actors increasingly dominate the market.

Future research will be aimed at investigating the broader implications of the Industry 4.0 transition beyond cloud services. Emerging digital tools such as AI and 3D printing have the potential to reshape firm performance, particularly in terms of size, productivity, and survival. Such an exploration would contribute to the understanding of the firm-level determinants of existing trends in productivity divergences and business dynamism, that have both been linked to digital intensity at the sector level (Calvino & Criscuolo 2019, Calvino et al. 2020, Corrado et al. 2021). Moreover, these technologies may yield different impacts depending on firm characteristics, as observed with cloud services, potentially accelerating or mitigating the aforementioned trends. Understanding how these new digital technologies interact with firm-specific factors is crucial, as technological adoption increasingly becomes a key determinant of market competitiveness in the current digital transition.

Acknowledgments
We thank Flavio Calvino, Marco Grazzi, and participants in the 2024 DRUID and 2024 EARIE congresses for insightful comments. Access to French data benefited from the use of Centre d'accès sécurisé aux données (CASD), which is part of the "Investissements d'Avenir" program (reference: ANR-10-EQPX-17) and supported by a public grant overseen by the French National Research Agency. Luca Fontanelli gratefully acknowledges funding from the European Union's Horizon 2020 research and innovation program under the ERC project grant agreement No. 853487 (2D4D). Usual caveats apply.

References

Acemoglu, D., Anderson, G. W., Beede, D. N., Buffington, C., Childress, E. E., Dinlersoz, E., Foster, L. S., Goldschlag, N., Haltiwanger, J. C., Kroff, Z., Restrepo, P. & Zolas, N. (2022), Automation and the workforce: A firm-level view from the 2019 annual business survey, Working Paper 30659, National Bureau of Economic Research.

Acemoglu, D. & Restrepo, P. (2020), 'Robots and jobs: Evidence from us labor markets', *Journal of Political Economy* **128**(6), 2188 – 2244.

Andersen, T. B., Bentzen, J., Dalgaard, C.-J. & Selaya, P. (2012), 'Lightning, IT diffusion, and economic growth across U.S. States', *Review of Economics and Statistics* **94**(4), 903–924.

Angrist, J. D. & Pischke, J.-S. (2008), *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton University Press.

Autor, D., Dorn, D., Katz, L. F., Patterson, C. & Van Reenen, J. (2020), 'The Fall of the Labor Share and the Rise of Superstar Firms*', *The Quarterly Journal of Economics* **135**(2), 645–709.
URL: *https://doi.org/10.1093/qje/qjaa004*

Babina, T., Fedyk, A., He, A. & Hodson, J. (2024), 'Artificial intelligence, firm growth, and product innovation', *Journal of Financial Economics* **151**, 103745.
URL: *https://www.sciencedirect.com/science/article/pii/S0304405X2300185X*

Bajgar, M., Berlingieri, G., Calligaris, S., Criscuolo, C. & Timmis, J. (2019), 'Industry concentration in Europe and North America', *Industrial and Corporate Change* .

Bajgar, M., Criscuolo, C. & Timmis, J. (2021), Intangibles and industry concentration: Supersize me, OECD Science, Technology and Industry Working Papers No. 2021/12, OECD Publishing, Paris.

Bessen, J. (2020), 'Industry concentration and information technology', *The Journal of Law and Economics* **63**(3), 531–555.
URL: *https://doi.org/10.1086/708936*

Bisio, L., Cuzzola, A., Grazzi, M. & Moschella, D. (2023), The dynamics of automation adoption: Firm-level heterogeneity and aggregate employment effects, LEM Papers Series 2023/37, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy.
URL: *https://ideas.repec.org/p/ssa/lemwps/2023-37.html*

Bloom, N. & Pierri, N. (2018), 'Cloud computing is helping smaller, newer firms compete', *Harvard Business Review* **51**(7).

Bontadini, F., Corrado, C., Haskel, J., Iommi, M. & Jona-Lasinio, C. (2023), 'Euklems & intanprod: industry productivity accounts with intangibles', *Sources of growth and productivity trends: methods and main measurement challenges, Luiss Lab of European Economics, Rome* .

Brynjolfsson, E. & Hitt, L. M. (2003), 'Computing Productivity: Firm-Level Evidence', *The Review of Economics and Statistics* **85**(4), 793–808.

Brynjolfsson, E., Jin, W. & Wang, X. (2023), Information Technology, Firm Size, and Industrial Concentration, NBER Working Papers 31065, National Bureau of Economic Research, Inc.

Brynjolfsson, E., McAfee, A., Sorell, M. & Zhu, F. (2008), Scale without mass: business process replication and industry dynamics, Technical Report Nov, Mimeo.

Brynjolfsson, E., Rock, D. & Syverson, C. (2018), Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics, *in* 'The Economics of Artificial Intelligence: An Agenda', NBER Chapters, National Bureau of Economics Research, pp. 23–57.

Byrne, D., Corrado, C. & Sichel, D. E. (2018), The rise of cloud computing: Minding your p's, q's and k's, Working Paper 25188, National Bureau of Economic Research.

Caldarola, B., Grazzi, M., Occelli, M. & Sanfilippo, M. (2023), 'Mobile internet, skills and structural transformation in rwanda', *Research Policy* **52**(10), 104871.
URL: *https://www.sciencedirect.com/science/article/pii/S0048733323001555*

Calvino, F. & Criscuolo, C. (2019), Business dynamics and digitalisation, OECD Science, Technology and Industry Policy Papers 62, OECD Publishing.
URL: *https://ideas.repec.org/p/oec/stiaac/62-en.html*

Calvino, F., Criscuolo, C. & Verlhac, R. (2020), Declining business dynamism: Structural and policy determinants, OECD Science, Technology and Industry Policy Papers 94, OECD Publishing.
URL: *https://ideas.repec.org/p/oec/stiaac/94-en.html*

Calvino, F. & Fontanelli, L. (2023*a*), Artificial intelligence, complementary assets and productivity: evidence from French firms, LEM Papers Series 2023/35, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy.

Calvino, F. & Fontanelli, L. (2023*b*), A portrait of AI adopters across countries: Firm characteristics, assets' complementarities and productivity, OECD Science, Technology and Industry Working Papers No. 2023/02, OECD Publishing, Paris.

Campa, J. M. & Kedia, S. (2002), 'Explaining the diversification discount', *The Journal of Finance* **57**(4), 1731–1762.

Cho, J., DeStefano, T., Kim, H., Kim, I. & Paik, J. H. (2022), 'What's driving the diffusion of next-generation digital technologies?', *Technovation* **119**.

Cirillo, V., Fanti, L., Mina, A. & Ricci, A. (2023), 'The adoption of digital technologies: Investment, skills, work organisation', *Structural Change and Economic Dynamics* **66**, 89–105.
URL: *https://www.sciencedirect.com/science/article/pii/S0954349X23000577*

Clougherty, J. A., Duso, T. & Muck, J. (2016), 'Correcting for self-selection based endogeneity in management research: Review, recommendations and simulations', *Organizational Research Methods* **19**(2), 286–347.

Corrado, C., Haskel, J. & Jona-Lasinio, C. (2021), 'Artificial intelligence and productivity: an intangible assets approach', *Oxford Review of Economic Policy* **37**(3), 435–458.

Coyle, D. & Nguyen, D. (2018), Cloud Computing and National Accounting, Economic Statistics Centre of Excellence (ESCoE) Discussion Papers ESCoE DP-2018-19, Economic Statistics Centre of Excellence (ESCoE).

Crémer, J., Biglaiser, G. & Mantovani, A. (2024), The Economics of the Cloud, TSE Working Papers 24-1520, Toulouse School of Economics (TSE).
URL: *https://ideas.repec.org/p/tse/wpaper/129265.html*

DeStefano, T. J., Teodorovicz, T., Cho, J., Kim, H. & Paik, J. (2022), 'What determines ai adoption?', *Academy of Management Proceedings* **2022**(1), 14791.

DeStefano, T., Kneller, R. & Timmis, J. (2023), 'Cloud Computing and Firm Growth', *The Review of Economics and Statistics* pp. 1–47.
URL: *https://doi.org/10.1162/rest_a_01393*

Domini, G., Grazzi, M., Moschella, D. & Treibich, T. (2021), 'Threats and opportunities in the digital era: Automation spikes and employment dynamics', *Research Policy* **50**(7).

Duso, T. & Schiersch, A. (2022), Let's Switch to the Cloud: Cloud Adoption and Its Effect on IT Investment and Productivity, CESifo Working Paper Series 9944, CESifo.

Gal, P., Nicoletti, G., von Rüden, C., Sorbe, S. & Renault, T. (2019), 'Digitalization and Productivity: In Search of the Holy Grail - Firm-level Empirical Evidence from European Countries', *International Productivity Monitor* **37**, 39–71.

Garrison, G., Wakefield, R. L. & Kim, S. (2015), 'The effects of it capabilities and delivery model on cloud computing success and firm performance for cloud supported processes and operations', *International Journal of Information Management* **35**(4), 377–393.

Goos, M. & Savona, M. (2024), 'The governance of artificial intelligence: Harnessing opportunities and mitigating challenges', *Research Policy* **53**(3), 104928.
URL: *https://www.sciencedirect.com/science/article/pii/S0048733323002123*

Grullon, G., Larkin, Y. & Michaely, R. (2019), 'Are US Industries Becoming More Concentrated?*', *Review of Finance* **23**(4), 697–743.
URL: *https://doi.org/10.1093/rof/rfz007*

Guriev, S., Melnikov, N. & Zhuravskaya, E. (2021), '3G Internet and Confidence in Government', *The Quarterly Journal of Economics* **136**(4), 2533–2613.
URL: *https://doi.org/10.1093/qje/qjaa040*

Gutiérrez, G. & Philippon, T. (2017), Declining Competition and Investment in the U.S, NBER Working Papers 23583, National Bureau of Economic Research, Inc.
URL: *https://ideas.repec.org/p/nbr/nberwo/23583.html*

Hamilton, B. H. & Nickerson, J. A. (2003), 'Correcting for endogeneity in strategic management research', *Strategic Organization* **1**(1), 51–78.

Harrigan, J., Reshef, A. & Toubal, F. (2021), 'The march of the techies: Job polarization within and between firms', *Research Policy* **50**(7).

Heckman, J. (1976), The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models, *in* 'Annals of Economic and Social Measurement, Volume 5, number 4', National Bureau of Economic Research, pp. 475–492.

Heckman, J. J. (1978), 'Dummy endogenous variables in a simultaneous equation system', *Econometrica* **46**(4), 931–959.

Jin, W. (2022), Cloud Adoption and Firm Performance: Evidence from Labor Demand, Technical Report Available at SSRN 4082436, SSRN.

Jin, W. & McElheran, K. (2019), Economies Before Scale: Survival and Performance of Young Plants in the Age of Cloud Computing, Rotman School of Management Working Paper No. 3112901, Rotman School of Management Working Paper No.

Kaplan, J. O. (2023), 'The World Wide Lightning Location Network (WWLLN) Global Lightning Climatology (WGLC) and time series'.
URL: *https://doi.org/10.5281/zenodo.10246857*

King, A. A. & Tucci, C. L. (2002), 'Incumbent entry into new market niches: The role of experience and managerial choice in the creation of dynamic capabilities', *Management Science* **48**(2).

Lashkari, D., Bauer, A. & Boussard, J. (2024), 'Information technology and returns to scale', *American Economic Review* **114**(6), 1769–1815.
URL: *https://www.aeaweb.org/articles?id=10.1257/aer.20220522*

Lu, Y., Phillips, G. M. & Yang, J. (2024), The impact of cloud computing and ai on industry dynamics and concentration, Working Paper 32811, National Bureau of Economic Research.
URL: *http://www.nber.org/papers/w32811*

Maddala, G. S. (1983), *Limited-Dependent and Qualitative Variables in Econometrics*, Cambridge University Press.

McElheran, K., Li, J. F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L. S. & Zolas, N. (2023), 'Ai adoption in america: Who, what, and where', *Forthcoming on the Journal of Economics and Management Strategy* .

Nicoletti, G., von Rueden, C. & Andrews, D. (2020), 'Digital technology diffusion: A matter of capabilities, incentives or both?', *European Economic Review* **128**(C).

OECD (2014), 'Cloud computing: The concept, impacts and the role of government policy', **No. 2014/240**.

Ohnemus, J. & Niebel, T. (2016), On the Determinants of Cloud Computing Adoption, 27th European Regional ITS Conference, Cambridge (UK) 2016 148694, International Telecommunications Society (ITS).

Puhani, P. (2000), 'The Heckman Correction for Sample Selection and Its Critique', *Journal of Economic Surveys* **14**(1), 53–68.

Schulman, A. & Spring, N. (2011), Pingin' in the rain, *in* 'Proceedings of the 2011 ACM SIGCOMM Conference on Internet Measurement Conference', IMC '11, Association for Computing Machinery, New York, NY, USA, p. 19–28.
URL: *https://doi.org/10.1145/2068816.2068819*

Shaver, J. M. (1998), 'Accounting for endogeneity when assessing strategy performance: Does entry mode choice affect FDI survival?', *Management Science* **44**(4), 571–585.

Ughi, A. & Mina, A. (2023), Digital advantage: Evidence from a policy evaluation of adoption subsidies, LEM Working Paper Series 2023/41, Scuola Superiore Sant'Anna, Laboratory of Economics and Management (LEM), Pisa.
URL: *https://hdl.handle.net/10419/297149*

Vella, F. & Verbeek, M. (1999), 'Estimating and interpreting models with endogenous treatment effects', *Journal of Business & Economic Statistics* **17**(4), 473–478.

Zolas, N., Kroff, Z., Brynjolfsson, E., McElheran, K., Beede, D. N., Buffington, C., Goldschlag, N., Foster, L. & Dinlersoz, E. (2020), Advanced technologies adoption and use by u.s. firms: Evidence from the annual business survey, Working Paper 28290, National Bureau of Economic Research.

A Appendix

Sales growth (long differences) by cloud type: OLS

Cloud type	Storage		Software		ICT	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Cloud	0.136***	0.405***	0.119***	0.471***	0.126***	0.639***
	(0.012)	(0.054)	(0.008)	(0.064)	(0.014)	(0.141)
Log Sales	-0.059***	-0.052***	-0.058***	-0.050***	-0.054***	-0.051***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Cloud*Log Sales		-0.027***		-0.034***		-0.048***
		(0.005)		(0.005)		(0.011)
Log Age	-0.105***	-0.105***	-0.106***	-0.106***	-0.107***	-0.107***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
ICT Share	0.361***	0.348***	0.361***	0.344**	0.371***	0.355**
	(0.108)	(0.110)	(0.111)	(0.113)	(0.116)	(0.118)
Log Physical Capital	0.016*	0.016*	0.017**	0.017**	0.017*	0.018**
	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
Log Intangible Capital	-0.010	-0.009	-0.010	-0.009	-0.010	-0.010
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Exporter	0.037***	0.036***	0.037***	0.036***	0.041***	0.040***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)
Multi-Plant	0.010	0.009	0.010	0.010	0.014	0.012
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Observations	14,605	14,605	14,605	14,605	14,605	14,605
R-squared	0.113	0.114	0.109	0.112	0.106	0.108
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Fe	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.108	0.110	0.105	0.107	0.101	0.104

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A1: Results of estimation Equation 2, for different cloud types

Employment growth (long differences): OLS and ET

	OLS		ET			
	Model 1	Model 2	Model 3		Model 4	
			Performance	Adoption	Performance	Adoption
Cloud	0.148***	0.195***	0.231***		0.314***	
	(0.012)	(0.033)	(0.021)		(0.017)	
Log Employment	-0.105***	-0.101***	-0.111***	0.216***	-0.108***	0.217***
	(0.006)	(0.007)	(0.006)	(0.012)	(0.007)	(0.012)
Cloud*Log Employment		-0.010*			-0.013***	
		(0.005)			(0.004)	
Log Age	-0.113***	-0.113***	-0.111***	-0.066***	-0.110***	-0.065***
	(0.005)	(0.005)	(0.005)	(0.013)	(0.005)	(0.013)
ICT Share	0.246*	0.242*	0.232**	0.457**	0.222*	0.457**
	(0.126)	(0.128)	(0.118)	(0.224)	(0.119)	(0.224)
Log Physical Capital	0.033***	0.033***	0.032***	0.029	0.032***	0.029
	(0.007)	(0.006)	(0.006)	(0.019)	(0.006)	(0.019)
Log Intangible Capital	-0.008	-0.008	-0.008	-0.015	-0.008	-0.014
	(0.005)	(0.005)	(0.005)	(0.018)	(0.005)	(0.018)
Exporter	0.029***	0.028***	0.024***	0.214***	0.022***	0.214***
	(0.008)	(0.008)	(0.008)	(0.028)	(0.008)	(0.028)
Multi-Plant	0.050***	0.049***	0.047***	0.097***	0.046***	0.097***
	(0.007)	(0.006)	(0.007)	(0.036)	(0.007)	(0.036)
Log Lighting Strike Density				-0.057***		-0.057***
				(0.012)		(0.012)
Observations	14,667	14,667	14,648	14,648	14,648	14,648
R-squared	0.129	0.130				
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Fe	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.125	0.125				

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A2: Results of estimation Equation 2, using long differences in employment growth as dependent variable and employment as the measure of size.

Sales growth (long differences): OLS and ET

	OLS		ET			
	Model 1	Model 2	Model 3		Model 4	
			Performance	Adoption	Performance	Adoption
Cloud	0.134***	0.235***	0.139***		0.282***	
	(0.011)	(0.019)	(0.019)		(0.030)	
Log Employment	-0.052***	-0.043***	-0.052***	0.208***	-0.046***	0.208***
	(0.005)	(0.005)	(0.006)	(0.013)	(0.006)	(0.013)
Cloud*Log Employment		-0.022***			-0.024***	
		(0.004)			(0.004)	
Log Age	-0.103***	-0.103***	-0.102***	-0.068***	-0.102***	-0.068***
	(0.006)	(0.006)	(0.006)	(0.013)	(0.006)	(0.013)
ICT Share	0.366***	0.355***	0.365***	0.463**	0.348***	0.463**
	(0.110)	(0.110)	(0.109)	(0.230)	(0.105)	(0.230)
Log Physical Capital	0.012	0.013	0.012	0.030	0.012	0.030
	(0.008)	(0.008)	(0.008)	(0.019)	(0.008)	(0.019)
Log Intangible Capital	-0.015**	-0.015**	-0.015***	-0.011	-0.015***	-0.011
	(0.005)	(0.005)	(0.005)	(0.018)	(0.005)	(0.019)
Exporter	0.023**	0.022**	0.023***	0.208***	0.019**	0.207***
	(0.008)	(0.008)	(0.008)	(0.028)	(0.008)	(0.028)
Multi-Plant	0.012	0.012	0.012	0.101***	0.010	0.100***
	(0.009)	(0.009)	(0.009)	(0.037)	(0.009)	(0.037)
Log Lighting Strike Density				-0.057***		-0.057***
				(0.012)		(0.012)
Observations	14,605	14,605	14,605	14,605	14,605	14,605
R-squared	0.108	0.110				
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Fe	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.104	0.105				

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A3: Results of estimation Equation 2, using long differences in sales growth as dependent variable and employment as the measure of size.

Sales growth (long differences, 10 years and 5 years): OLS and ET

	OLS (2005)		ET (2005)				OLS (2009)		ET (2009)			
	Model 1	Model 2	Model 3		Model 4		Model 5	Model 6	Model 7		Model 8	
			Performance	Adoption	Performance	Adoption			Performance	Adoption	Performance	Adoption
Cloud	0.225***	0.610***	0.290***		0.982***		0.103***	0.290***	0.078***		0.308***	
	(0.020)	(0.133)	(0.046)		(0.152)		(0.009)	(0.043)	(0.020)		(0.037)	
Log Sales	-0.123***	-0.110***	-0.127***	0.187***	-0.126***	0.192***	-0.038***	-0.032***	-0.037***	0.194***	-0.033***	0.194***
	(0.008)	(0.009)	(0.009)	(0.011)	(0.012)	(0.012)	(0.003)	(0.004)	(0.003)	(0.010)	(0.004)	(0.010)
Cloud*Log Sales		-0.039***			-0.047***			-0.019***			-0.019***	
		(0.011)			(0.010)			(0.004)			(0.004)	
Log Age	-0.128***	-0.128***	-0.126***	-0.064***	-0.123***	-0.061***	-0.079***	-0.079***	-0.079***	-0.064***	-0.079***	-0.064***
	(0.005)	(0.005)	(0.005)	(0.013)	(0.004)	(0.014)	(0.006)	(0.006)	(0.006)	(0.015)	(0.006)	(0.015)
ICT Share	0.402***	0.388***	0.395***	0.272*	0.355***	0.273*	0.286**	0.277**	0.291***	0.607***	0.274***	0.607***
	(0.066)	(0.068)	(0.063)	(0.149)	(0.054)	(0.147)	(0.096)	(0.097)	(0.097)	(0.165)	(0.095)	(0.165)
Log Physical Capital	0.014	0.017*	0.014	0.013	0.016*	0.010	0.017*	0.017*	0.017*	0.030*	0.017*	0.029*
	(0.009)	(0.008)	(0.009)	(0.013)	(0.008)	(0.014)	(0.009)	(0.009)	(0.009)	(0.017)	(0.009)	(0.017)
Log Intangible Capital							-0.014	-0.013	-0.014*	-0.011	-0.013*	-0.010
							(0.008)	(0.008)	(0.008)	(0.011)	(0.008)	(0.010)
Exporter	0.036**	0.033*	0.032*	0.179***	0.018	0.175***	0.019**	0.017*	0.020**	0.195***	0.016**	0.195***
	(0.016)	(0.016)	(0.017)	(0.035)	(0.018)	(0.034)	(0.008)	(0.008)	(0.008)	(0.030)	(0.008)	(0.030)
Multi-Plant	0.042***	0.041***	0.039***	0.119***	0.030***	0.114***	-0.004	-0.005	-0.003	0.135***	-0.005	0.135***
	(0.011)	(0.011)	(0.011)	(0.029)	(0.010)	(0.029)	(0.006)	(0.006)	(0.006)	(0.034)	(0.006)	(0.034)
Log Lighting Strike Density				-0.066***		-0.067***				-0.052***		-0.052***
				(0.015)		(0.016)				(0.010)		(0.010)
Observations	12,568	12,568	12,568	12,568	12,568	12,568	14,248	14,248	14,248	14,248	14,248	14,248
R-squared	0.178	0.180					0.084	0.086				
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.173	0.175					0.0792	0.0804				

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A4: Results of estimation equations 2 and 3, using long differences as in Acemoglu & Restrepo (2020)

Sales growth (long differences as in Acemoglu & Restrepo (2020)): OLS and ET

	OLS (2005)		ET (2005)				OLS (2009)		ET (2009)			
	Model 1	Model 2	Model 3		Model 4		Model 5	Model 6	Model 7		Model 8	
			Performance	Adoption	Performance	Adoption			Performance	Adoption	Performance	Adoption
Cloud	0.320***	0.631***	0.394***		0.802***		0.174***	0.424***	0.161***		0.454***	
	(0.030)	(0.122)	(0.038)		(0.095)		(0.024)	(0.051)	(0.033)		(0.049)	
Log Sales	-0.127***	-0.115***	-0.133***	0.230***	-0.124***	0.230***	-0.073***	-0.064***	-0.072***	0.241***	-0.066***	0.241***
	(0.009)	(0.007)	(0.009)	(0.012)	(0.007)	(0.012)	(0.009)	(0.008)	(0.009)	(0.013)	(0.007)	(0.013)
Cloud*Log Sales		-0.032***			-0.035***			-0.025***			-0.026***	
		(0.010)			(0.008)			(0.006)			(0.006)	
Log Age	-0.118***	-0.120***	-0.117***	-0.069***	-0.117***	-0.069***	-0.111***	-0.112***	-0.111***	-0.073***	-0.111***	-0.073***
	(0.005)	(0.005)	(0.004)	(0.013)	(0.004)	(0.013)	(0.006)	(0.006)	(0.006)	(0.012)	(0.006)	(0.012)
ICT Share	0.357***	0.345***	0.355***	0.363***	0.333***	0.363***	0.467***	0.459***	0.470***	0.502***	0.455***	0.504***
	(0.077)	(0.077)	(0.077)	(0.135)	(0.079)	(0.135)	(0.108)	(0.106)	(0.108)	(0.189)	(0.102)	(0.190)
Log Physical Capital	0.004	0.006	0.003	0.016	0.005	0.015	0.027*	0.027*	0.027**	0.035	0.027**	0.035
	(0.005)	(0.004)	(0.005)	(0.013)	(0.004)	(0.013)	(0.013)	(0.013)	(0.013)	(0.022)	(0.013)	(0.022)
Log Intangible Capital							-0.019	-0.017	-0.019*	-0.020	-0.018	-0.020
							(0.012)	(0.011)	(0.012)	(0.024)	(0.011)	(0.024)
Exporter	0.021	0.017	0.018	0.162***	0.011	0.162***	0.033*	0.030*	0.033**	0.175***	0.029*	0.174***
	(0.014)	(0.014)	(0.014)	(0.030)	(0.014)	(0.030)	(0.016)	(0.015)	(0.016)	(0.029)	(0.015)	(0.029)
Multi-Plant	0.025	0.025	0.020	0.165***	0.017	0.164***	0.004	0.003	0.005	0.164***	0.002	0.165***
	(0.020)	(0.019)	(0.021)	(0.019)	(0.020)	(0.019)	(0.009)	(0.009)	(0.009)	(0.026)	(0.009)	(0.027)
Log Lighting Strike Density				-0.078***		-0.078***				-0.067***		-0.068***
				(0.015)		(0.015)				(0.014)		(0.014)
Observations	12,521	12,521	12,503	12,503	12,503	12,503	13,715	13,715	13,696	13,696	13,696	13,696
R-squared	0.168	0.169					0.122	0.123				
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.162	0.164					0.117	0.118				

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A5: Results of estimation equations 2 and 3, using long differences as in Acemoglu & Restrepo (2020)

Sales growth, long differences including cloud purchases in years 2019 and 2020: OLS and ET

	OLS (2019)		ET (2019)				OLS (2020)		OLS (2020)			
	Model 1	Model 2	Model 3		Model 4		Model 5	Model 6	Model 7		Model 8	
			Performance	Adoption	Performance	Adoption			Performance	Adoption	Performance	Adoption
Cloud	0.140***	0.429***	0.12122***		0.47674***		0.143***	0.418***	0.12932***		0.45380***	
	(0.0139)	(0.0630)	(0.02415)		(0.06409)		(0.0156)	(0.0876)	(0.03435)		(0.10133)	
Log Sales	-0.0634***	-0.0527***	-0.06186***	0.18569***	-0.05420***	0.18584***	-0.0648***	-0.0534***	-0.06367***	0.18618***	-0.05463***	0.18618***
	(0.00194)	(0.00177)	(0.00224)	(0.00830)	(0.00182)	(0.00832)	(0.00376)	(0.00161)	(0.00488)	(0.00812)	(0.00179)	(0.00814)
Cloud * Log Sales		-0.0295***			-0.03061***			-0.0285***			-0.02927***	
		(0.00530)			(0.00509)			(0.00732)			(0.00727)	
Share of ICT Hours	0.392***	0.379***	0.40111***	0.57579***	0.37612***	0.57532***	0.362***	0.351***	0.37293***	0.62058***	0.35175***	0.62008***
	(0.0775)	(0.0793)	(0.07702)	(0.20837)	(0.07460)	(0.20917)	(0.0514)	(0.0547)	(0.05225)	(0.21893)	(0.05272)	(0.21965)
Log Age	-0.110***	-0.111***	-0.11080***	-0.08349***	-0.11014***	-0.08351***	-0.119***	-0.120***	-0.11891***	-0.09317***	-0.11873***	-0.09334***
	(0.00680)	(0.00679)	(0.00685)	(0.01083)	(0.00677)	(0.01107)	(0.00965)	(0.00968)	(0.00932)	(0.01196)	(0.00935)	(0.01218)
Log Physical Capital	0.0152	0.0157	0.01541	0.03030**	0.01551*	0.03001**	0.0154	0.0159	0.01555	0.03166***	0.01578	0.03152***
	(0.00947)	(0.00914)	(0.00957)	(0.01272)	(0.00912)	(0.01291)	(0.0106)	(0.0104)	(0.01074)	(0.01183)	(0.01045)	(0.01188)
Log Intangible Capital	-0.0100	-0.00879	-0.01038	-0.00583	-0.00916	-0.00545	-0.0126	-0.0113	-0.01286	-0.00362	-0.01155	-0.00338
	(0.00819)	(0.00821)	(0.00841)	(0.01247)	(0.00829)	(0.01274)	(0.0101)	(0.0102)	(0.01021)	(0.00975)	(0.01032)	(0.00988)
Exporter	0.0384***	0.0366***	0.03882***	0.18106***	0.03406***	0.18051***	0.0433***	0.0413***	0.04364***	0.18505***	0.03926***	0.18480***
	(0.00925)	(0.00965)	(0.00916)	(0.02528)	(0.00946)	(0.02532)	(0.00811)	(0.00842)	(0.00849)	(0.02149)	(0.00860)	(0.02153)
Multiplant	0.0127	0.0123	0.01392*	0.14860***	0.01077	0.14853***	0.0211***	0.0207***	0.02209***	0.15281***	0.01952***	0.15292***
	(0.00725)	(0.00782)	(0.00735)	(0.02653)	(0.00773)	(0.02659)	(0.00667)	(0.00655)	(0.00652)	(0.01913)	(0.00668)	(0.01917)
Log Lighting Density (2008-2017)				-0.05769***		-0.05787***				-0.05574***		-0.05594***
				(0.00829)		(0.00822)				(0.00738)		(0.00736)
Observations	20,658	20,658	20,622	20,622	20,622	20,622	27,581	27,581	27,532	27,532	27,532	27,532
R-squared	0.131	0.133					0.149	0.151				
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.128	0.130					0.146	0.148				

Table A6: Results of estimation Equations 2 and 3, using long differences including the information on cloud purchases in years 2019 and 2020

Cloud and Concentration

	Baseline		Weighted	HH 4-digit	Cloud Share			
					<50	<100	<250	250+
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Cloud Share	-0.760**	-0.480***	-0.453**	-0.378***	-0.571**	-0.496**	-0.446**	-0.008
	(0.314)	(0.170)	(0.214)	(0.097)	(0.274)	(0.222)	(0.189)	(0.270)
Log ICT Intensity	0.061	0.270*	0.250	0.064	0.239	0.264*	0.267*	0.309*
	(0.043)	(0.145)	(0.178)	(0.092)	(0.143)	(0.144)	(0.144)	(0.158)
Log Total Sales	0.191***	0.543**	1.078**	0.811***	0.628***	0.589***	0.548**	0.404
	(0.066)	(0.218)	(0.486)	(0.182)	(0.215)	(0.207)	(0.225)	(0.281)
Log Total Employment	-0.275***	-1.208	-2.183*	-0.264	-1.206	-1.240	-1.180	-1.115
	(0.077)	(0.814)	(1.102)	(0.543)	(0.787)	(0.799)	(0.815)	(0.846)
Observations	118	118	118	118	118	118	118	118
Ind. FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.0764	0.629	0.669	0.744	0.638	0.632	0.629	0.618

Table A7: Full estimation result of Equation 6. Model 1 and 2 use the HH index computed at the 2-digit level, Model 3 weights observations by the market share of sectors, Model 4 estimates the 2-digit HH as the weighted average of the HH at the 4-digit level, Model 5-8 estimate the share of firms adopting cloud in firms below 50, 100 and 250 employees, or in firms with more than 250 employees.