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Cátia Cerqueira

Fernando Alexandre

Miguel Portela

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Universidade do Minho
Escola de Economia e Gestão

Digitalization: the edge of first movers*

C. Cerqueira[†] F. Alexandre[‡] M. Portela[§]

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Abstract

This paper examines firms' characteristics and the impact on firm performance of being a first mover in the adoption of cloud computing and big data digital technologies, relative to followers and non-adopters. Our results show that firms with higher levels of education both for managers and workers, and shorter managerial tenure are more likely to be digital adopters. First movers in the adoption of big data show distinct characteristics from followers, namely they are younger and have a larger share of higher education workers. Regarding the impact on firm performance, we find that first movers in cloud computing experience significant performance gains, namely in gross value added and productivity, compared to non-adopters, but no gains relative to followers. Interestingly, first movers in big data exhibit a productivity edge over followers and non-adopters. Furthermore, we find that higher levels of education and shorter managerial tenure amplify the positive effects of big data adoption on firm performance.

Keywords: cloud computing, big data, management, digitalization, productivity, ICT.

JEL Classification: *D24, M10, E22, E23, J24, O33, L20*

1 Introduction

This paper investigates firms' characteristics that favour the adoption of digital technologies, namely cloud computing and big data, and their impact on firm performance. Our analysis shed light on the potential benefits of being a first mover in the adoption of digitalization.

Digitalization has significantly reshaped the business landscape, triggering profound changes in processes and markets. As a result, several transformative economic trends

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[†]NIPE/Universidade do Minho.
[‡]NIPE/Universidade do Minho.
[§]NIPE/Universidade do Minho and IZA Bonn.

have emerged, such as increased productivity dispersion, the rise of superstar firms, market concentration, reduced business dynamism, and the growing importance of intangible assets (Andrews et al., 2015, 2016). Understanding the critical factors that facilitate firms' successful adoption of these technologies and their effective implementation to achieve productivity gains is paramount, especially for economies striving to catch up with more advanced counterparts. Digitization, while offering tremendous opportunities, requires time and necessitates complementary innovations, investments in intangible capital, organizational changes, and the development of essential skills (Brynjolfsson et al., 2017; Berlingieri et al., 2020; Calvino et al., 2022). The interplay of these factors influences the outcomes of digital adoption and its subsequent impact on firm performance (Calvino and Fontanelli, 2023). Several works have shown that management plays a pivotal role in enabling the adoption of new technologies and enhancing productivity by implementing innovative processes and fostering dynamic organizational cultures (Giorcelli, 2019; Koch et al., 2021; Calvino and Fontanelli, 2023; Garicano, 2015; Bloom et al., 2012).

The timing of technology adoption within industries and firms has been a subject of considerable research interest. Firms that fall behind in embracing specific technologies may witness declining profits, as competitors leverage these technologies to gain a competitive edge through more efficient production processes (Acemoglu et al., 2023). Moreover, the adoption of particular technologies at a specific juncture plays a pivotal role in facilitating the assimilation of future technologies. For instance, research by Niebel et al. (2019) highlights that the adoption of big data increases the inclination for innovation and leads to higher levels of innovation intensity, underscoring the complementary nature of intangible assets that these technologies bring. Additionally, Engelstätter (2012) discovered that the implementation of enterprise software systems enhances the likelihood of future innovation. However, embracing digital technology as an early adopter carries also risks stemming from the inherent uncertainty and unpredictability of new technologies. Innovators commit substantial resources without the benefit of historical data or well-established best practices, leaving them vulnerable to unforeseen hurdles, such as technical glitches and compatibility issues. Consequently, comprehending the performance impacts and determinants of technological adoption in cohorts is vital for discerning if there is potential competitive advantages enjoyed by early adopter firms.

This paper contributes to the literature on the link between digitalization and firm performance. First, this paper identifies firms' characteristics that influence the decision adopt digital technologies and to be a first mover. Specifically, we assess the role of factors such as the education of managerial teams and workers, manager teams experience or firms' age. Second, this research corroborates previous findings that highlight the benefits, namely to firm productivity, of embracing new technologies. Nevertheless, this study goes beyond the existing literature by showing the potential benefits of being a first mover in the adoption of two kinds of digital technologies. Therefore, the third contribution of this paper is to shed light on the potential benefits of being a first mover in the adoption of different types of digital technologies. Finally, this study emphasizes the critical role of human capital in mediating the benefits of digital technologies to firm performance. Our findings underscore the importance of timing, firm and digital technological characteristics, and human capital in determining the success of digitalization. Such knowledge is critical for businesses and policymakers aiming to capitalize on digital technologies and navigate the ever-changing digital landscape successfully.

The remainder of this paper is organized as follows. In section 2, we provide a comprehensive literature review, synthesizing relevant studies on technology adoption, its impacts on firm performance, and the role of management. Section 3 presents the data, variables, and descriptive statistics used in the econometric analysis. Section 4 outlines the methodology employed in these study. Section 5 presents the results of our estimations. Finally, section 6 concludes the paper, summarizing the key findings and suggesting implications for policymakers and firm managers.

2 Literature review

The widespread global adoption of the internet in the 1990s brought about a revolutionary transformation in communication and work methodologies, resulting in higher levels of efficiency for firms. This digital revolution facilitated the emergence of complex technologies such as cloud computing and big data, leading to dynamic and unpredictable markets. However, the adoption of these technologies requires societal adaptation and preparedness (Brynjolfsson and McAfee, 2014). This includes the need to realign workers' skills with complementary technologies (Brynjolfsson and McAfee, 2012), redefine and decentralize firms' organizational structures (Bresnahan et al., 2002), and maintain competitive markets (Andrews et al., 2016).

In recent years, there has been a notable increase in productivity growth attributed to technology, dispelling previous uncertainties (Stiroh, 2002). However, the impact of technology on labor productivity is not as straightforward as it appears. Acemoglu et al. (2014) argue that the observed positive effects can be attributed to a decline in employment rather than an increase in value-added, particularly excluding computer production in the manufacturing sector due to its ubiquity. Additionally, national productivity measures may not fully capture the true impact of technology due to measurement limitations (Brynjolfsson et al., 2021). General-purpose technologies require significant complementary investments, such as the co-invention of new processes, business models, and human capital, which are difficult to measure and can result in under reported value-added (Brynjolfsson et al., 2021).

The presence of crucial intangible assets that are accessible only to a select group of firms contributes to the rise of superstar firms and may explain the productivity slowdown (Andrews et al., 2016; Autor et al., 2020). Berlingieri et al. (2020) find that younger firms with more skilled workers experience slower catch-up in industries with high utilization of digital technologies, indicating challenges in technology and knowledge transfer. Policymakers play a vital role in ensuring equitable dissemination of technology to all firms for the benefit of society as a whole (Andrews et al., 2015).

Numerous studies have investigated the impacts of technological adoption on firms' performance. One early study by Stoneman and Kwon (1996) found that new technologies can increase firm profits by an average of 11%, but the magnitude of this impact varies depending on firm and industry characteristics and the extent of technology dissemination. Subsequent studies have identified several key characteristics of adopting firms that strongly influence the effects of technologies. These include management quality, firm size, human capital composition, intangible assets, and learning spillovers Bloom and Van Reenen (2007); Bartel et al. (2007); Bartelsman et al. (2013); Wu et al. (2022); Segarra-Blasco et al. (2022). Specifically concerning the influence of ICT technologies on productivity, the studies conducted by Cette et al. (2022) for French firms, Hall et al. (2013) for Italian firms, and Amador and Silva (2023) for Portuguese firms unanimously demonstrate a positive effect of technology adoption on labor productivity and TFP.

Management quality plays a crucial role in the decision to adopt technology and in maximizing its positive impact on firm performance (Garicano, 2015; Bloom et al., 2019; Daveri and Parisi, 2015). Better management quality is associated with larger, more efficient firms that experience faster growth and higher survival rates (Bloom and Van Reenen, 2007; Bloom et al., 2012; Alexandre et al., 2021). Skilled managers are better prepared to recognize technological opportunities, possess the necessary intangible assets and human capital skills, and navigate the changes brought about by technology adoption (Bartelsman et al., 2013; Bresnahan et al., 2002; Garicano, 2015; Bloom et al., 2019). Improved management skills amplify the impact of new technology and lead to long-term benefits (Giorcelli, 2019; Wu et al., 2022). The adoption of new IT-enhanced machinery improves workforce organization and management, resulting in enhanced efficiency throughout the production process (Bartel et al., 2007). Daveri and Parisi (2015) observed that managerial age has a negative effect on firms' performance in innovative firms. At the aggregate level, there is a strong correlation between IT and management practices, stimulating income and productivity growth (Schivardi and Schmitz, 2019).

Larger firms, benefiting from economies of scale, have a higher likelihood of adopting new technologies as they possess the necessary investments and human skills (Koch et al., 2021; Garicano, 2015). Exporters are also more inclined to adopt new technologies, driven by increased competition. The pressure to enhance productivity and the potential for economies of scale contribute to this trend (Koch et al., 2021; Calvino and Fontanelli, 2023). Spillover effects have been identified as significant drivers of innovation (Audretsch and Belitski, 2020; Calvino et al., 2018; Ballestar et al., 2020).

Studies on technology adoption also highlight the significance of non-managerial workers' abilities in managing procedures and utilizing digital information for successful adoption and firm performance. Highly skilled workers in micro and small firms tend to experience greater productivity returns from technological adoption (Calvino et al., 2022), and improving worker skills is crucial for reaping the benefits of new technologies (Barbosa and Faria, 2022).

In conclusion, the study of technological adoption and its effects at both the firm and aggregate levels is a complex endeavor. It requires consideration of various factors, including technology type, sector, economic context, and firm characteristics. The literature emphasizes the need for improved data to better understand the complexities involved (Comin and Mestieri, 2014). As emerging technologies like artificial intelligence continue to shape our society, ongoing debates and research are necessary to comprehend their full potential and consequences. The profound impacts of these technologies on firms and society fuel our dedication to further investigate and contribute to this evolving discourse.

3 Data and variables description

This section provides a description of the database and a discussion of the descriptive statistics.

3.1 Data

The data used in this study comes from three main sources. The Information and Communication Technologies Usage and e-commerce in Enterprises (IUTICE), the Integrated Business Accounts System (SCIE) provided by Statistics Portugal (INE), and the Personnel Records database (QP) provided by Ministry of Labor, Solidarity and Social Security (MTSSS). These three datasets are linked through a common anonymized identifier.

The SCIE dataset includes comprehensive information on firms' balance sheets and financial statements for all non-financial firms starting from 2006 (about 350,000 firms per year). It results from integrating statistical information on companies, primarily based on administrative data, with a focus on simplified business information. This dataset provides valuable firm-level data on economic and financial indicators.

The QP dataset provides information on the Portuguese labor force and is collected yearly since 1986 by MTSSS. It covers all private firms, establishments, and employees in Portugal, amounting to approximately 3 million workers and 350 thousand firms each year. This dataset offers detailed worker-level information on various employee characteristics, such as tenure, educational level, monthly earnings, hours worked, occupation, and identification of the employing firm.

The main database utilized in this study is IUTICE, an annual stratified probability sample survey provided by the INE. The IUTICE is a survey implemented since 2004, focusing on the adoption of information and communication technologies and e-commerce by firms. It forms part of the Eurostat Community Survey on ICT Usage and e-commerce in Enterprises. This statistical survey aims to enhance our comprehension of the adoption of information and communication technologies in the business sector, as well as to examine the significance and prioritization of these technologies in relation to overall economic competitiveness.

The IUTICE survey gathers data from a representative sample of companies in Portugal, operating in the sectors of manufacturing, energy, construction, trade and repair, accommodation and catering, transport and communications, and other services (excluding education, health activities, and financial activities). Large firms with over 250 workers or total revenues exceeding 25 million euros are surveyed comprehensively, while smaller firms are sampled using a stratified random approach based on the number of workers, turnover, and economic activity. To account for the over-representation of large-sized firms, sampling weights are provided in the survey. Participation in the IUTICE survey is mandatory for selected firms. IUTICE is an unbalanced dataset with approximately seven thousands firms each year.

IUTICE has three distinct weights: one based on the number of firms, another on the number of workers, and a third on turnover. According to the survey's methodology, the weight based on the number of firms should be assigned to the majority of the variables considered in the survey. This weight is determined by the inverse probability of a company being selected for inclusion in the sample. The second weight is designed for variables related to the number of workers, while the third weight pertains to variables related to turnover. The sample selection weight, as discussed in Heeringa et al. (2017), ensures that our sample accurately represents the target population. Unbiased estimation of the population distribution requires the weighting of sample data when population elements have varying probabilities of being included in the sample, as is the case here (Heeringa et al., 2017).

Therefore, in this study, all inferences and estimations are derived using sample survey weights. The weight for the number of firms is used for descriptive statistics and the analysis of adoption probabilities. The turnover weight is employed to assess the impacts of technology on productivity and turnover. Additionally, the weight for the number of workers is applied in examining the effects of technology on employment.

The initial IUTICE dataset has information on 39,411 firms, covering the period between 2014 and 2019. To align with the objectives of our study, we excluded firms that reported non-use of the internet. This led to a dataset comprising 3,821 firms, resulting in the exclusion of 574 to 786 firms annually. Consequently, the revised dataset retained a total of 35,590 observations, representing 22,805 individual firms. Upon integrating the IUTICE data with the QP and SCIE datasets, using anonymized identifiers, there was a reduction of 4,202 observations compared to the original IUTICE dataset. Additionally, after combining the datasets, 497 observations were missing in both the QP and SCIE datasets, whereas 3,705 observations were exclusive to QP. As a result, our final dataset comprised 19,828 unique firms. For this set of firms, we collected data from QP and SCIE for the years 2006 to 2019. It is worth noting that we excluded the agriculture and mining industries, as the IUTICE dataset does not cover these sectors. The ultimate firm-level panel dataset consists of 238,717 observations.

3.2 Variable description

In this study, we focus on two digital technologies: cloud computing, surveyed in 2014, 2016, 2017, and 2018; and big data, surveyed in 2016 and 2018.

Cloud computing refers to internet-based ICT services that provide access to software, storage capacity, and computing power, among other features. It operates through a global network of servers located worldwide. These servers are designed to manage data and enable the execution of applications and content accessible from anywhere, at any time, via the internet. Cloud computing offers advanced security and file recovery capabilities. Firms can customize their usage, acquiring the necessary space and functionality without additional hardware investments. This empowers firms of all sizes to securely store and manage files, data, documents, and applications, resulting in faster access compared to traditional reliance on personal computers and manual file transfers. The adoption of cloud computing enhances management efficiency, protecting firm information and enabling seamless adaptability to expansion, contraction, or new international strategies without the need for complex hardware investment projects. In this study, cloud computing includes the use office software, file and database storage, accounting or finance applications, customer relationship management, and running their own software (excluding firms that solely utilize cloud computing for email services).

Big data refers information gathered from firm-owned sensors or smart devices, geolocation data from portable devices, data generated from digital media (e.g., social media), and other unspecified sources. Big data is characterized by three main attributes: volume (large quantities of data generated over time), variety (diverse formats of complex data, both structured and unstructured, such as text, videos, images, voice, documents, sensor data, etc.), and velocity (the rapid pace at which data is generated and undergoes changes over time). Firms employ big data technologies to collect, process, and analyze data, aiming to identify patterns, trends, and insights. This process involves specialized software tools, algorithms, and analytical skills to manage and interpret the data. The adoption of big data can enhance operational efficiency, customer targeting, decision-making processes, and other aspects. Examples of big data applications include targeted retail offers, GPS navigation assistance, and business intelligence. It is worth noting that big data often requires significant data storage and processing capabilities, frequently leveraging cloud computing infrastructure.

We define first movers as those firms that adopted each technology in its inaugural year of inclusion in the IUTICE survey: cloud computing was included in 2014 and big data in 2016. However, we should note that these technologies could have been already in use in previous years, which limits the precision of our definition of first movers. Nevertheless, considering the relatively low adoption rates among first movers (6.76% for cloud computing and 9.67% for big data), alongside Portugal's non-pioneering position in technology adoption, we believe our definition is adequate to identify first movers. Follower firms are identified as those that adopt the technology in the subsequent waves of the survey. Non-adopter firms are those that have never reported the usage of the technology in all waves of the survey.

Another dimension relevant to our analysis are the competences of the managerial team on the decision to adopt cloud computing and big data technologies. Executive decisions are not solely made by the general manager or CEO, but rather by a group of managers who report to the administration board as high-level directors or key senior managers (Bloom and Reenen, 2011; Carpenter, 2002). Therefore, the variable "Manager" has been constructed by selecting all top managers, namely CEOs and executive directors, as well as all firms' highest-level department directors. This definition is based on occupational categories as defined in the CNP94 national occupational classification (for the period before 2010) and in the CPP2010 occupational classification (starting in 2010). In the CNP94 national classification of occupations, individuals categorized as members of the management team include those holding positions as public administration managers (code 11), corporate managers (code 12), and general managers of small businesses (code 13). In the CPP2010 national classification of occupations, members of the management team encompass managing directors and chief executives (code 112), administrative and commercial managers (code 121 and code 122), production and specialized services managers (code 131 to 134), as well as hospitality, retail, and other services managers (code 141 to 143).

Concerning the impact of digital technologies, we consider the following variables: gross value added (GVA), turnover, employment, labor productivity (LP), measured by ratio of value-added over the number of workers, and total factor productivity (TFP). TFP is computed following Ackerberg et al. (2015).

Table 1 provides a comprehensive description of all variables used in this study.[1]

[1]For the purposes of classification, we define micro firms as those with fewer than 10 workers and turnover and total assets equal to or less than 2 Million Euros. Small firms have less than 50 employees (with a minimum of ten) and turnover and total assets equal to or less than 10 Million Euros. Medium-sized firms employ between 50 and 250 workers, with turnover ranging from 10 Million to 50 Million Euros and total assets between 10 Million and 43 Million Euros. Large firms have more than 250 workers, turnover exceeding 50 Million Euros, and total assets surpassing 43 Million Euros.

Table 1: Variable description

Variable	Description	Source
Average education of manager	Managers' team average years of education.	QP
Previous management experience	Managers' team average years of experience as manager in former firms.	QP
Share High Educ Managers	The proportion of managers with a degree (%).	QP
Average manager tenure	Managers' average tenure at the company.	QP
Size	Micro, Small, Medium, and Large are determined by combining the number of employees, total sales, and total assets.	SCIE
Number of workers / Employment	Number of employees reported by the company each year.	SCIE
Share of high educated workers	Employees (non-managers) with a college diploma. (%)	QP
Education of workforce	Workers' average years of education (excluding managers).	QP
Labor productivity (LP)	$\frac{\text{Value added}}{\text{Number of workers}}$	SCIE
Gross value added (GVA)	Gross Value Added.	SCIE
Total factor productivity (TFP)	TFP was calculated in the manner described by Ackerberg et al (2015).	SCIE
Profitability	$\frac{\text{EBIT}}{\text{Total Assets}}$	SCIE
Capital intensity	$\frac{\text{Real Fixed Assets}}{\text{Number of workers}}$	SCIE
Average wages	$\frac{\text{Real Labor Costs}}{\text{Number of Workers}}$	SCIE
Leverage	$\frac{\text{Total Liabilities}}{\text{Total Assets}}$	SCIE
Turnover	Volume of sales and services provided	SCIE
Exporter	Dummy variable that takes the value 1 if the firm exports at least 10 % of total sales for three consecutive years.	SCIE
Importer	Dummy variable that takes the value 1 if the firm imports at least 10 % of total purchases for three consecutive years.	SCIE
Foreign owned	Dummy variable with a value of 1 if the firm is more than 50% owned by foreigners and zero otherwise.	QP
Firm age	The number of years since the year of the constitution.	QP
Investment in fixed assets	$\frac{\text{Investment in Fixed Assets}}{\text{Total Assets}}$	SCIE
Share of computer users	$\frac{\text{Number of Computer Users}}{\text{Number of Workers}}$	SCIE and IUTICE
Young firm	Dummy variable that takes the value of 1 if the firm is 10 years old or less, and 0 otherwise.	QP

Notes: SCIE stands for Integrated Business Accounts System QP stands for Personnel Records and UTICE stands for Information and Communication Technologies usage and e-commerce in enterprises.

3.3 Descriptive statistics

In this section we present and discuss a set of descriptive statistics for the variables underlying our empirical analysis. Table 2 presents the adoption rates for each technology, categorized by firm size. In 2014, the initial reporting year for cloud computing, 6.8% of firms adopted that technology. Adoption rates increase with firm size. The digital adoption rate was 5.7% for micro-sized firms, 7.7% for small-sized firms, 10.5%

for medium-sized firms, and 15.2% for large-sized firms. In 2016, big data technology was adopted by 9.7% of the firms in the IUTICE survey. As in the cloud computing technology, the big data adoption rates increase with firm size: 8.2% for micro-sized firms, 11.2% for small-sized firms, 15.4% for medium-sized firms and 20.6% for large-sized firms. This pattern is observed in all waves of the survey. This finding aligns with existing literature, which highlights the positive correlation between technology adoption and firm size (Koch et al., 2021; Calvino and Fontanelli, 2023; Berlingieri et al., 2020). Table 2 also show increasing adoption rates of cloud computing over time, overall and by firm size. For the sample including all firms, the incidence of cloud computing increased from 6.7% in 2014 to 14.5% in 2018. For the population of large firms, there was an increase from 15.2% in 2014 to 47.7% in 2018.

However, the upward trend over time, except for large-size firms, is not observed for the big data technology.[2] Nevertheless, while the adoption rate for big data decreases for micro-, small-, and medium-sized firms, it shows a significant increase (by 9.3 percentage points) for large-sized firms from 2016 to 2018.

[2]Official reports from the National Institute of Statistics (INE) indicate a rise in big data adoption over time, excluding micro-sized firms. When we exclude micro-sized firms in our analysis, we arrive at the same adoption rate as reported by INE. This occurs due to micro firms being omitted in international/official reports due to data limitations from other countries. However, INE confirmed that we can include micro firms in our analysis since the collected data accurately represents the micro-Portuguese firm population. Given that micro firms constitute the majority, we opted to include them in our analysis.

Table 2: Percentage of firms that have adopted technology, broken down by size and year (%)

	2014	2016	2017	2018
Panel A: all firms				
Cloud computing	6.76	10.42	12.14	14.53
Big data		9.67		8.53
Panel B: micro firms				
Cloud computing	5.74	8.13	9.42	10.99
Big data		8.22		6.28
Panel C: small firms				
Cloud computing	7.65	12.92	13.52	17.34
Big data		11.23		10.97
Panel D: medium firms				
Cloud computing	10.50	19.32	25.19	27.76
Big data		15.42		14.08
Panel E: large firms				
Cloud computing	15.24	27.57	41.96	47.74
Big data		20.60		29.90
Number of firms	4,584	5,238	5,549	5,422

Notes: We report the percentage of adopters of each technology among the groups of firms divided by size in panels B to E. Cloud computing technology is surveyed in 2014, 2016, 2017, and 2018; and Big data in 2016 and 2018. This report uses sampling weights provided by the survey.

Source: Authors' calculations based on IUTICE, INE.

When analyzing the adoption rate of cloud computing by industry,[3] our data show that the 'information and communication services sector' has the highest adoption rate. For example, in 2018, 46.0% of firms in that sector adopted cloud computing. That adoption rate was closely followed by the 'other services: repair of computers and communication equipment sector', with an adoption rate of 34.2%, and the 'water, sanitation, waste management and depollution', which recorded a rate of 30.5%. Moreover, when considering only the firms that adopted cloud computing, the largest share (26.6%) came from the 'wholesale and retail sector', primarily from the 'wholesale sector'. 'Manufacturing industries' ranked as the third-highest sector in terms of cloud computing adopters, accounting for 15.3%, preceded by 'consulting, scientific, technical, and similar services', with an adoption rate of 18.6%.

Concerning big data technology, the sectors with the highest adoption rates, in 2018,

[3]For a detailed analysis, see Appendix A.1

were 'water, sanitation, waste management, and depollution' (20.9%), 'electricity, gas, steam and cold air' (20.8%), and 'information and communication services' (20.6%). When examining the distribution of big data adopters by sector, the largest percentage of adopters, comprising 29.3%, was once again observed in the 'wholesale and retail sector' (specifically in the sub-sector of retail). This was followed by 'manufacturing industries' (17.1%) and 'consulting, scientific, technical, and similar services' (12.9%).

Tables 3 and 4 provide descriptive statistics for cloud computing and big data, respectively. These tables classify firms into three categories: non-adopters, first movers and followers.

Concerning cloud computing, Table 3, we observe that non-adopters have the lowest mean investment in fixed assets (77 thousand euros) compared to first movers (323 thousand euros) and followers (363 thousand euros). The education level of managers and the workforce, measured in years of education, is consistent across the three groups, with mean values around 11 to 13. However, first movers and followers have a higher proportion of highly educated managers and workers compared to non-adopters, suggesting that firms adopting cloud computing tend to employ a more educated workforce. The tenure of managers is quite similar across the three categories, with only slight variations in mean values. Non-adopters have the lowest percentage of foreign-owned firms (3%), while followers have the highest (7%). First movers and followers have a significantly higher mean number of workers (48 and 54, respectively) compared to non-adopters (15). Both first movers and followers exhibit a substantially higher mean turnover (7,771 thousand euros and 9,692 thousand euros) and gross value added (1,900 thousand euros and 2,141 thousand euros) compared to non-adopters (1,915 in turnover and 440 in gross value added), indicating that adopting firms are larger. First movers and followers also have a higher percentage of computer users compared to non-adopters, with mean values of 68% and 73%, respectively.

Table 3: Descriptive statistics: cloud computing

	Non adopters		First Movers		Followers	
	Mean	P50	Mean	P50	Mean	P50
Investments in fixed assets (in ths)	77	2	323	2	363	9
Firm age	19	16	17	13	19	16
Average wage (in ths)	16	13	18	15	21	17
Capital intensity (in ths)	46	7	62	6	43	7
Education of managers	11	11	13	13	13	13
Education of workforce	10	9	11	11	11	11
Exporter (%)	7	0	7	0	9	0
Foreign owned (%)	3	0	6	0	7	0
Leverage (%)	84	62	72	66	86	63
Previous management experience	0	0	0	0	1	0
Number of workers	15	6	48	7	54	9
Productivity (in ths)	29	18	35	20	37	23
Profitability (%)	2	4	3	4	-42	5
Share high educ. managers (%)	25	0	46	50	49	50
Share high educ workers (%)	10	0	20	8	22	11
Tenure managers	13	12	11	10	12	11
Turnover (in ths)	1915	338	7711	487	9692	591
Gross value added (in ths)	440	100	1900	160	2141	206
Share of computer users (%)	60	56	68	75	73	88

Notes: We report all years of the sample. Sampling weights provided by the survey are used in this report. P50 stands for Percentil 50. ”ths” stands for thousands.”

Source: Authors’ calculations based on IUTICE, QP and SCIE, INE.

Regarding big data technology, Table 4, it is worth noting that non-adopters have a lower mean investment in fixed assets (81 thousand euros) compared to first movers (257 thousand euros) and followers (515 thousand euros). However, it is interesting to observe that the median values for all three categories are relatively low, suggesting a significant variation in asset investments within each group. The education level of managers and the workforce shows minimal variation across the three groups, with mean values around 10 to 12 years of schooling. First movers and followers have a higher proportion of highly educated managers and workers compared to non-adopters. The share of export on total turnover are slightly higher for first movers (10%) and followers (10%) compared to non-adopters (7%). Non-adopters have the lowest percentage of foreign-owned firms (3%), while followers have the highest (7%). Followers also have the highest mean number of workers (63) compared to first movers (39) and non-adopters (17). Managerial tenure is relatively consistent across the three categories, with only minor variations in mean values. Both first movers and followers exhibit significantly higher mean values for turnover and gross value added compared to non-adopters, indicating that adopting firms are larger. The percentage of computer users is relatively consistent across the three categories, with minor variations in mean values.

Table 4: Descriptive statistics: big data

	Non adopters		First Movers		Followers	
	Mean	P50	Mean	P50	Mean	P50
Investments in fixed assets (in ths)	81	2	257	8	515	11
Firm age	19	16	18	15	19	16
Average wage (in ths)	16	14	16	14	19	16
Capital intensity (in ths)	41	6	36	8	80	9
Education of managers	11	11	12	12	12	12
Education of workforce	10	9	10	10	11	11
Exporter (%)	7	0	10	0	10	0
Foreign owned (%)	3	0	4	0	7	0
Leverage (%)	93	61	88	65	65	65
Previous management experience	1	0	1	0	1	0
Number of workers	17	6	39	8	63	9
Productivity (in ths)	29	19	32	20	43	22
Profitability (%)	-8	4	3	4	6	5
Share high educ. managers (%)	27	0	38	0	39	0
Share high educ. workers (%)	11	0	16	3	18	7
Tenure managers	13	12	11	10	12	11
Turnover (in ths)	2100	345	6649	556	12524	692
Gross value added (in ths)	481	106	1559	149	2715	224
Share of computer users (%)	64	67	63	67	71	83

Notes: We report all years of the sample. Sampling weights provided by the survey are used in this report. "ths" stands for thousands."

Source: Authors' calculations based on IUTICE, QP and SCIE, INE.

Notably, the descriptive statistic reveals that non-adopters of cloud computing and big data differ significantly from adopters, whether they are first movers or followers, in some key characteristics: they have lower levels of investment in fixed assets, employ workers and managers with lower levels of education, have a smaller proportion of managers and workers possessing college degrees, are smaller in terms of size (measured through number of workers, turnover, and gross value added), and show a lower inclination to foreign ownership. The differences among adopters, first movers and followers, are not pronounced in terms of magnitude, but key distinctions exist for both technologies. Notably, firms that adopted cloud computing and big data early tend to be slightly younger in age and have managers with less tenure compared to followers.

4 Methodology and econometric strategy

This paper aims at characterizing firms adopting digital technologies and to evaluate the impact of digital technologies on the performance of firms. In this section, we outline the baseline models and methodology used in our estimations, taking into account the specific characteristics of our panel and the objectives of our study.

4.1 Characterization of digital adopters

To investigate the determinants of digitalization adoption, we focus on cloud computing and big data, that are defined as categorical variables. These variables take the values of 0, 1 and 2 to indicate the firm's digitalization adoption behavior. A value of 1 represents early adoption, or first mover, while 2 denotes later adoption, or follower, and 0 indicates non-adoption. We our analysis we employ a Multinomial Logit Model to analyze the digitalization adoption patterns. The probability formula for our model is presented in equation (1).

$$P(Y_{i,t} = j | X_{i,t-2}, Z_{i,t-2}) = \frac{\exp\left[X'_{i,t-2}\beta + Z'_{i,t-2}\sigma\right]}{\sum\limits_{j=0}^{2} \exp\left[X'_{i,t-2}\beta + Z'_{i,t-2}\sigma\right]}, \quad j = 0, 1, 2. \tag{1}$$

In this equation, X represents the characteristics related to human capital, such as managers or workers, while Z denotes the control variables, including size and sector dummies, Leverage, Profitability, and Exporter Status. The variable j represents the choice of adoption, which can be non-adoption, first mover, or follower adopter. It's important to highlight that odds ratios in the multinomial logit model are self-contained and can be individually interpreted in comparison to the remaining outcomes. In our results tables, we present the margins effects (at the means for continuous variables and at the base category for categorical variables, as specified in the results table notes). These margins effects reveal the difference in probability for each outcome level associated with a one-unit change in each predictor variable. Importantly, this difference is computed independently for each outcome level and remains unaffected by the base outcome specified in the mlogit model.

Our hypothesis is that various factors, including the education level of the managerial team, the education level of the workforce, and other relevant variables captured in a vector denoted as X, can explain the decision to adopt technology. It is important to note that our independent variables are lagged by two years. This adjustment is necessary because the IUTICE survey, which serves as the source of our dependent variable, is reported by firms at the beginning of the year. In contrast, the independent variables are derived from the QP and SCIE surveys, which reflect the firm's position at the end of the year and are collected in the subsequent year.

4.2 The impact of digitalization on firm performance

In our analysis of how digital adoption affects firm performance, we utilized a range of dependent variables. These variables encompassed gross value-added, turnover, employment, labor productivity, and TFP, all of which were measured using logarithmic values. To establish a causal connection between technological adoption and firm performance, it is crucial to ensure a random selection of technology adoption. This requires that the groups subjected to technology adoption and those not exposed to it are nearly identical, with the only discernible difference over time being the introduction of technology within our framework, in addition to our modeled variables.

Nevertheless, we acknowledge that the treated and non-treated groups are not identical. Firms with superior performance tend to invest more in innovation, increasing their likelihood of adopting new technologies(Daveri and Parisi, 2015; Koch et al., 2021). This introduces selection issues since the two groups under study exhibit dissimilarities. While the fixed effects specification handles selection based on time-invariant characteristics, it is vital to recognize that firm attributes can evolve over time due to factors unrelated to the model, thus influencing technology adoption decisions.

To address this concern, we adopt the approach outlined by Guadalupe et al. (2012) and reweight firms using a propensity score estimator. This technique considers variations in the probability of adoption based on prior characteristics.

The propensity score is calculated by distinguishing between firms that adopt technology in year t as treated observations, and firms that never adopt technology as control observations. Separate propensity scores are computed for each technology. To estimate the probability of firm i being a technological adopter, we pool treated and control observations from all years, accounting for exporter status, size, and capital stock (lagged by two years). The estimated probability is derived using sample survey weights, reflecting the number of firms in the sample. The resulting propensity score, denoted as p is employed to assign weights to the treated and control firms. Specifically, each treated firm is assigned a weight of $1/p$ while each control firm is assigned a weight of $1/(1-p)$.

The reweighted estimator of the propensity score is utilized in equations (2) and (4). This estimation assumes that technology adoption is random and depends on observable characteristics that may vary over time, influencing the selection process. The choice of the propensity score reweighting estimator, as opposed to the propensity score matching estimator, is justified by the findings of Busso et al. (2014), which demonstrate the superior performance of reweighting over propensity score matching in finite samples.

First movers versus non-adopters

Let $Y_{i,t}$ represent our five dependent variables for firm i in time t. Hence, the model we adopt is presented in equation (2):

$$\begin{aligned} \ln(Y)_{i,t} = \beta_4 FMAdopter_{i,t-1} + \beta_5 X_{i,t-1} + \\ \beta_6 Z_{i,t-1} + \hat{\alpha}_i + \eta_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

Where FMAdopter represents a binary variable that take the value of 1 if firm i is a first mover into digital technology at time $t-1$, and 0 otherwise. X is a vector of explanatory variables related to human capital characteristics, and Z is a vector of control variables (exporter, leverage, foreign owned, importer, firm age squared, weight of computer users, sector and size). Due to its definition, being first mover is a constant within firms, which implies that we cannot use the standard panel data fixed effect models. In light of the extensive information captured in our datasets and following the approach proposed by Torres et al. (2018), we adopt a cross-section model with an additional control variable representing the firm-specific non-time-varying component. This component is generated through the prediction of the fixed effect in a previous model. The model used for predicting the fixed effect, denoted as $\hat{\alpha}_i$, is presented in equation (3).

$$\ln(Y)_{i,t} = \beta_4 TecAdopter_{i,t-1} + \alpha_i + \eta_t + \varepsilon_{i,t} \tag{3}$$

The variable $TecAdopter$ is a binary variable that takes a value of 1 if firm i is using any of three new technologies that is part of IUTICE inquiry at time t, namely cloud computing, big data or robotics.

Since we have incorporated a predicted parameter, we employ the bootstrap technique to ensure valid statistical inference in the second step of the analysis (equation 2). The application of bootstrap is discussed in detail in Cameron and Trivedi (2005), specifically in chapter 6.6.

First movers versus followers

To study the differences between first movers and follower adopters, we utilized a Long-Differences Model that aims to capture the variations in performance measures between these two groups. The model was employed for the study of cloud computing from 2013 to 2019. In this context, first movers of cloud computing are firms that adopted cloud technology in 2014, while the followers reported their usage of the technology in subsequent years. Similarly, the long differences for big data were analyzed from 2015 to 2019.

Let Y_i represent our 5 dependent variables, our long-differences estimation equation is defined in equation (4).

$$\Delta(Y_i) = \beta_4 TecFMAdopter_i + \beta_2 X_{i,t*} + \beta_3 Z_{i,t*} + \varepsilon_i \tag{4}$$

Were, $\Delta(Yi)$ represents the differences in our dependent variables between the end and the beginning of the employed long-differences panel. $TecFMAdopter_i$ is a dummy variable that takes the value of 1 for first mover firms and 0 for follower. $X_{i,t*}$ denotes a set of explanatory variables related to human capital characteristics established at the beginning of the Long-Differences panel ($t*$), $Z_{i,t*}$ represents a set of control variables (exporter, leverage, foreign owned, importer, firm age squared, weight of computer users, sector and size) and ε_i represents the error term.

5 Results

In this section, we present the results of our two main research questions: (1) What are the characteristics that distinguish of first movers from followers and non-adopters of digital technologies? and (2) Is there an edge of first movers into digital technologies on firm performance?

5.1 Characterization of digital adopters

Table 5 presents the results for the first question of our study. The table shows the marginal effects resulting from the estimation of the multinomial logit model presented in equation (1). The table is organized with columns 1 to 3 representing cloud computing technology and columns 4 to 6 for big data technology. Marginal effects for the outcome of non-adoption (NAdopter) in cloud computing and big data are presented in columns 1 and 4, respectively. Columns 2 and 5 contain the outcomes for first-mover adopters (FMover), while columns 3 and 6 are for followers. Panels A to G represent different models estimated with varying firm characteristics, analyzed separately due to endogeneity concerns.

The first notable result to highlight is that the characteristics of digital non-adopters (columns 1 and 4 in Table 5) are markedly distinct from those who adopt digital technologies, whether they are first movers or followers. Non-adopters are more likely to have lower levels of education among managers and workers, longer managerial tenures, and represent older firms when compared to those adopting digital technologies. This finding is aligned with the ones reported in Calvino et al. (2022), Daveri and Parisi (2015), Calvino and Fontanelli (2023), among others.

Secondly, although we observe differences in the magnitude of the coefficients, the characteristics that drive firms to adopt cloud computing earlier are similar to those that prompt followers to adopt that digital technology (columns 2 and 3 in Table 5). However, when it comes to big data adoption, some distinctions emerge in the characteristics of firms at different stages of adoption. Specifically, our results suggest that firms with shorter managerial tenures and a higher proportion of college-educated workers are more likely to be pioneers in adopting big data technology compared to the remaining possible outcomes (column 5 of Table 5). Those same characteristics have no significant impact on the likelihood of becoming a follower adopter (column 6 of Table 5). However, hypothesis testing to determine differences between first movers and follower adopters of big data shows that there are no significant statistical differences in the impact of those characteristics between these two groups.

Looking at the results reported in Table 5, we should stress that past managerial experience (panel D of Table 5) increases the probability of being a follower in both technologies relative to non-adopting or being a first mover (a one-year increase in years of experience increases the probability of follower adoption of cloud computing and big data by 0.6 p.p. and 0.4 p.p., respectively). These result suggests that the inclination to become a follower in the adoption of digital technologies may be explained by managerial experiences in previous firms, while the decision to be a first mover or non-adopter is inherent and potentially influenced by the firms' culture and a well-defined strategy based on previous investments. However, for big data, hypothesis testing does not allow us to reject the possibility that both first movers and followers are equally impacted by past managerial experience.

Our findings, as detailed in panels E and F of Table 5, reveal that workers' education plays a significant role in the adoption of digital technologies. In particular, the level of education appears to be a key determinant in becoming a first mover in big data technology and a follower in cloud computing technology.

Finally, being a young firms is a particularly relevant characteristic to adopt advanced digital technologies, independently of the stage of adoption (panel G of Table

5). Hypothesis testing for the equality of marginal effects indicate that being a young firm has no distinguishable impact on the likelihood of becoming either a first mover or a follower adopter, for both technologies.

Focusing on first movers, the coefficients of marginal effects (columns 2 and 5 of Table 5) enables us to draw several key conclusions. A one-year increase in the average years of education of managers raises the probability of first mover adopting cloud computing and big data by 0.2 p.p., compared to the remaining possible outcomes (non-adoption or follower). An increase of one percentage point in the share of managers with higher education levels increases the probability of early adoption of cloud computing by 0.01 p.p., at a 10% significance level. However, it does not significantly impact the probability of adopting big data technology. Furthermore, a one-year increase in managerial tenure has a negative impact on the probability of being a first mover, reducing it by 0.07 p.p. for cloud computing and by 0.11 p.p. f. or big data. The effects of average years of education among workers have a slightly larger magnitude compared to managers' education. A one-year increase in workers' education positively impacts the probability of being a first mover by 0.3 p.p. for cloud computing and 0.5 p.p. for big data. Similarly, the share of workers with a diploma follows the same probability impact trends. Being a young firm appears to affect the probability of being a first-mover in adopting big data, showing an impact of 2.4 percentage points, which is statistically significant at the 5% significance level. Being a young firm also impact positively the probability of adopt cloud computing earlier, by 0.8 p.p., though this effect is only statistically significant at the 10% level.

These findings provide insights that warrant further exploration of the literature on complementary intangible assets (Calvino and Fontanelli, 2023; Calvino et al., 2022), particularly regarding the role of human capital skills. This aspect will fuel our subsequent section of results, where we will delve into the relationship between firms' performance and the potential complementary of human capital.

Table 5: Selection into digitalization adoption - multinomial logit analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Cloud Computing			Big Data		
	NAdopter	FMover	Follower	NAdopter	FMover	Follower
	Panel A					
Education manager	-0.0091***	0.0015***	0.0076***	-0.0040***	0.0024**	0.0015*
	(0.0010)	(0.0004)	(0.0009)	(0.0013)	(0.0009)	(0.0009)
	Panel B					
Share HE manager	-0.0006***	0.0001*	0.0005***	-0.0002*	0.0001	0.0001
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	Panel C					
Tenure manager	0.0017***	-0.0007***	-0.0010**	0.0017***	-0.0011**	-0.0006
	(0.0005)	(0.0002)	(0.0004)	(0.0006)	(0.0005)	(0.0004)
	Panel D					
Prev. manager exper.	-0.0035	-0.0020	0.0055**	-0.0048	0.0009	0.0039**
	(0.0026)	(0.0015)	(0.0021)	(0.0030)	(0.0024)	(0.0019)
	Panel E					
Education workers	-0.0141***	0.0026***	0.0116***	-0.0086***	0.0051***	0.0035***
	(0.0014)	(0.0006)	(0.0012)	(0.0020)	(0.0016)	(0.0012)
	Panel F					
Share HE workers	-0.0015***	0.0003***	0.0012***	-0.0009***	0.0007***	0.0002
	(0.0002)	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
	Panel G					
Young firm	-0.0223**	0.0084*	0.0139*	-0.0390***	0.0239**	0.0151*
	(0.0093)	(0.0048)	(0.0083)	(0.0129)	(0.0099)	(0.0089)
Obs		15,747			8,170	

Notes: A value of 0 indicates that the firm is a non-adopter (NAdopter, columns 1 and 4), a value of 1 indicates that the firm is a technological first mover adopter (FMover, columns 2 and 5), and a value of 2 indicates that the firm is a technological follower adopter (columns 3 and 6). The model used in this study is a multinomial logit (mlogit) model. It includes dummies for sector and size, and controls for Profitability, Leverage, and Exporter. The table displays marginal effects calculated using mean values for continuous variables (panels A to F) and the base category for the dummy variable 'Young Firm' in panel G. The standard errors reported are robust, and they are presented in parentheses. The survey's sampling weights are used. Significant levels: ***, 1%; **, 5%; *, 10%.
Source: Authors' calculations based on IUTICE, QP and SCIE, INE.

5.2 The impact of digitalization on firm performance

The second research question of our study aims to examine the impact of cloud computing and big data adoption on firm performance. In our analysis we also explore potential complementary between technology and management characteristics. Specifically, we will estimate the impact on five dependent variables, namely on gross value-added, turnover, employment, labor productivity, and TFP (all measured in logarithmic form). We will analyze how these firm performance measures are affected by different cohorts of digital adoption. As in our previous analysis, we will focus on three groups: first mover adopters, followers and non-adopters. For each digital technology, we will first examine the impact on firm performance of being a first mover compared to a non-adopter. Subsequently, we will apply a long-differences model, similar to the approach found in the research of Acemoglu et al. (2023) and Daveri and Parisi (2015), to investigate whether there are any differential impacts of technology adoption on firm performance depending on the cohort of adoption, specifically distinguishing between first movers and followers.

Cloud computing

The results of our econometric estimation of the impact of the adoption of cloud computing by first movers, presented in Table 6, show significant positive effects on firm performance. Specifically, these pioneering firms have experienced substantial improvements across various performance indicators. Prior to the inclusion of the interaction term (columns 1, 3, 5, 7, and 9 in Table 6), our findings indicate a 12% increase in GVA, a 10% boost in turnover, a 6% rise in employment, a 7% enhancement in labor productivity, and a 4% increase in TFP for first movers in comparison to non-adopters.

Furthermore, when we consider the interaction between cloud computing adoption and human capital characteristics (columns 2, 4, 6, 8 and 10 in Table 6) we do not find any evidence of a complementary relationship between the managerial team education and cloud computing on firm performance. These findings are in line with the results reported in Gal et al. (2019), providing consistent evidence in this regard.

When we estimate the long differences model to assess whether there are any differences in the impact of cloud computing adoption between first movers and followers (as shown in Table 7), our analysis suggests that there are no distinguishable differences in these two groups.

Table 6: First movers versus non-adopters, the impact of cloud computing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	GVA		Turnover		Employment		LP		TFP	
					Panel A					
Education manager$_{t-1}$	0.0001	0.0002	-0.0002	-0.0006	0.0006	0.0004	-0.0010	-0.0006	-0.0019	-0.0011
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cloud computing FM$_{t-1}$	0.1227***	0.1339*	0.0831***	0.0412	0.0633***	0.0444	0.0697***	0.1149*	0.0410***	0.1203
	(0.014)	(0.070)	(0.011)	(0.064)	(0.010)	(0.041)	(0.011)	(0.066)	(0.012)	(0.073)
CCFM$_{t-1}$ × EM$_{t-1}$		-0.0008		0.0031		0.0014		-0.0033		-0.0058
		(0.005)		(0.005)		(0.003)		(0.005)		(0.005)
					Panel B					
Tenure manager$_{t-1}$	0.0021***	0.0018***	-0.0002	-0.0002	0.0009**	0.0007**	0.0013**	0.0012**	0.0006	0.0006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Cloud computing FM$_{t-1}$	0.1254***	0.1046***	0.0828***	0.0819***	0.0647***	0.0502**	0.0708***	0.0621***	0.0406***	0.0400*
	(0.014)	(0.026)	(0.011)	(0.026)	(0.010)	(0.021)	(0.011)	(0.019)	(0.011)	(0.023)
CCFM$_{t-1}$ × TM$_{t-1}$		0.0017		0.0001		0.0012		0.0007		0.0000
		(0.002)		(0.002)		(0.001)		(0.001)		(0.002)
					Panel C					
Prev manager exper$_{t-1}$	-0.0038	-0.0057	0.0141***	0.0107*	0.0043	0.0023	-0.0091*	-0.0097*	-0.0083*	-0.0089*
	(0.005)	(0.006)	(0.005)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)
Cloud computing FM$_{t-1}$	0.1231***	0.1183***	0.0816***	0.0729***	0.0632***	0.0581***	0.0700***	0.0685***	0.0407***	0.0393***
	(0.013)	(0.014)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.012)	(0.011)	(0.013)
CCFM$_{t-1}$ × PME$_{t-1}$		0.0083		0.0149		0.0088		0.0025		0.0025
		(0.014)		(0.015)		(0.008)		(0.011)		(0.010)
					Panel D					
Education workers$_{t-1}$	0.0004	-0.0002	0.0014	0.0025	-0.0014	-0.0010	-0.0002	-0.0012	-0.0008	-0.0018
	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Cloud computing FM$_{t-1}$	0.1225***	0.0906**	0.0821***	0.1355***	0.0645***	0.0829**	0.0694***	0.0186	0.0404***	-0.0126
	(0.014)	(0.039)	(0.012)	(0.044)	(0.010)	(0.033)	(0.011)	(0.031)	(0.011)	(0.033)
CCFM$_{t-1}$ × EW$_{t-1}$		0.0029		-0.0048		-0.0017		0.0046		0.0048
		(0.004)		(0.004)		(0.003)		(0.003)		(0.003)

Notes: All dependent variables are in logs. LP stands for labor productivity. TFP stands for total factor productivity. Coefficients were obtained using Propensity Score Reweighting Estimator with sampling weights and bootstrap standard errors. Controls for exporter activity, leverage, foreign ownership status, importer activity, firm age, and computer user share were applied to all models. In the models for labor productivity, we also control for capital stock, intermediate inputs, and the number of employees. In the remaining models we also control for size. The total number of observations is 3,366. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Authors' calculations based on IUTICE, QP and SCIE, INE.

Table 7: First movers versus followers in cloud computing, long-term performance impact

	(1)	(2)	(3)	(4)	(5)
	ΔGVA	ΔTurnover	ΔEmployment	ΔLP	ΔTFP
			Panel A		
Education manager	0.0197*	0.0251*	0.0087	0.0091	0.0116
	(0.011)	(0.013)	(0.009)	(0.008)	(0.007)
CC FM adopters	-0.0287	-0.0187	0.0119	-0.0482	-0.0424
	(0.049)	(0.046)	(0.041)	(0.036)	(0.033)
			Panel B		
Tenure manager	-0.0167***	-0.0119***	-0.0127***	-0.0028	-0.0005
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
CC FM adopters	-0.0342	-0.0229	0.0080	-0.0493	-0.0429
	(0.049)	(0.046)	(0.041)	(0.036)	(0.033)
			Panel C		
Prev. manager exper	0.0822***	0.0746***	0.0438*	0.0388**	0.0376**
	(0.025)	(0.024)	(0.024)	(0.019)	(0.017)
CC FM adopters	-0.0229	-0.0136	0.0151	-0.0453	-0.0398
	(0.049)	(0.046)	(0.041)	(0.036)	(0.033)
			Panel D		
Education workers	0.0189	0.0075	0.0292*	-0.0054	0.0027
	(0.018)	(0.016)	(0.016)	(0.011)	(0.009)
CC FM adopters	-0.0317	-0.0204	0.0081	-0.0479	-0.0431
	(0.049)	(0.046)	(0.041)	(0.036)	(0.032)

Notes: Dependent variables are in logs. LP stands for labor productivity. TFP stands for total factor productivity. The coefficients were obtained using long differences model 2013-2019 with Propensity Score Reweighted Estimator. Sampling weights were used. Controls for exporter activity, leverage, foreign ownership status, importer activity, firm age, and computer user share were applied to all models. In the models for labor productivity, we also account for capital stock, intermediate inputs, and the number of employees, as well as size in the remaining models. Robust standard errors are in parenthesis. The total number of observations is 908. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Authors' calculations based on IUTICE, QP and SCIE, INE.

Big data

Table 8 contains the results of estimating the impact of early adoption of big data on firm performance, in comparison to non-adopters. In the odd-numbered columns across all panels (A to D), we observe a consistent positive effect of early big data adoption. Firms that embrace big data technology experience a 10% increase in GVA, a 7% boost in turnover, a 4% rise in employment, a 6% improvement in labor productivity, and a 4% increase in TFP.

Turning to the even-numbered columns in Panel A (Table 8), where we consider the interaction between managerial characteristics and big data adoption, several key findings emerge. Firstly, there is a positive coefficient for the interaction between managers' education levels and big data adoption, particularly when explaining employment and TFP in column 10. This suggests that firms with well-educated managerial teams can reap the benefits of big data technology, and higher education levels enhance this positive impact. Specifically, a one-year increase in a manager's education level results in a 0.4 percentage point increase in the positive effects of early adoption. On the other hand, we notice a slight negative effect in column 6, where the education level of the managerial team interacts with big data adoption and impacts employment. This could be attributed to improved organizational methods resulting from enhanced managerial skills, leading to increased efficiency and consequently dampening the positive effects of big data technology on employment (Bloom et al., 2012; Calvino and Fontanelli, 2023).

In Panel B (Table 8), the relationship between managers' tenure and big data adoption on various performance metrics is explored. A one-year increase in managers' tenure results in a reduction of the positive effects of big data adoption on GVA, turnover, labor productivity, and TFP by 0.19 percentage points, 0.33 percentage points, 0.17 percentage points, and 0.15 percentage points, respectively. It's worth noting that the positive impact of big data technology will persist in firms with the most tenured managers; it will only be reduced.

Moving on to Panel C (Table 8), we observe a positive interaction between past managerial experience and big data adoption on turnover. Firms benefit from the combination of experienced managers and the utilization of big data, resulting in an increased positive impact of early adoption on turnover by 0.73 percentage points.

Finally, in Panel D (Table 8), we consider the education levels of workers. Similar to the managerial education, we find a significant positive coefficient for the interaction term in models for firms' productivity in columns 8 and 10. This indicates that firms can only harness the productivity gains associated with big data technology if they have a workforce with a certain level of education. This positive impact is observed in both labor productivity and TFP, by 0.48 percentage points and 0.40 percentage points, respectively, with the latter being statistically significant at the 10% significance level.

In summary, the findings on Table 8 emphasize the importance of managerial and workforce characteristics and their interactions with big data adoption in shaping firm performance outcomes. These results align with the expectations outlined in existing literature, including studies of Niebel et al. (2019), Schivardi and Schmitz (2019), Daveri and Parisi (2015), and others, providing further support for the notion that firms with higher human capital levels are more likely to benefit from technological implementations, leading to improved performance outcomes.

When examining the long differences model that compares the performance of first movers into big data technology with followers, presented in Table 9), our analysis uncovers significant differences. Firms that embraced big data technology early on (first movers) experienced substantially more positive impacts on GVA, LP, and TFP compared to those who adopted it at a later stage. Specifically, these pioneering firms witnessed notable improvements in GVA, LP, and TFP by approximately 10%, 8%, and 5%, respectively. These findings highlight the edge of being a first mover in the adoption of big data technology, as it leads to significantly enhanced performance outcomes.

Table 8: First movers versus non-adopters, the impact of big data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	GVA		Turnover		Employment		LP		TFP	
					Panel A					
Educ manager$_{t-1}$	0.0022***	0.0020**	0.0006	0.0004	0.0005	0.0010	0.0012*	0.0008	0.0012*	0.0006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Big data FM$_{t-1}$	0.0997***	0.0789***	0.0672***	0.0543**	0.0448***	0.0805***	0.0589***	0.0299	0.0358***	-0.0153
	(0.007)	(0.024)	(0.008)	(0.021)	(0.006)	(0.014)	(0.006)	(0.019)	(0.006)	(0.020)
BD$_{t-1}$ × EM$_{t-1}$		0.0016		0.0010		-0.0027***		0.0022		0.0038**
		(0.002)		(0.002)		(0.001)		(0.002)		(0.002)
					Panel B					
Tenure manager$_{t-1}$	-0.0004	-0.0001	-0.0005	0.0002	-0.0001	0.0000	-0.0002	0.0001	-0.0003	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Big data FM$_{t-1}$	0.1002***	0.1240***	0.0668***	0.1079***	0.0449***	0.0527***	0.0591***	0.0797***	0.0362***	0.0553***
	(0.008)	(0.014)	(0.008)	(0.018)	(0.006)	(0.011)	(0.006)	(0.009)	(0.006)	(0.009)
BD$_{t-1}$ × TM$_{t-1}$		-0.0019**		-0.0033***		-0.0006		-0.0017***		-0.0015***
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
					Panel C					
Prev manager exper$_{t-1}$	0.0019	0.0006	0.0026*	0.0004	0.0023**	0.0019	-0.0001	-0.0010	-0.0008	-0.0020
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Big data FM$_{t-1}$	0.1005***	0.0967***	0.0670***	0.0610***	0.0447***	0.0434***	0.0595***	0.0569***	0.0367***	0.0333***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.006)	(0.005)	(0.006)	(0.007)	(0.006)	(0.007)
BD$_{t-1}$ × PME$_{t-1}$		0.0047		0.0073**		0.0015		0.0032		0.0041
		(0.004)		(0.003)		(0.002)		(0.004)		(0.004)
					Panel D					
Educ workers$_{t-1}$	0.0036**	0.0027	0.0009	0.0010	0.0022***	0.0024***	0.0026**	0.0016	0.0007	-0.0002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Big data FM$_{t-1}$	0.1001***	0.0570**	0.0673***	0.0706***	0.0446***	0.0523***	0.0588***	0.0071	0.0364***	-0.0071
	(0.007)	(0.024)	(0.008)	(0.021)	(0.006)	(0.015)	(0.007)	(0.021)	(0.006)	(0.021)
BD$_{t-1}$ × EW$_{t-1}$		0.0040		-0.0003		-0.0007		0.0048**		0.0040*
		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)

Notes: All dependent variables are in logs. LP stands for labor productivity. TFP stands for total factor productivity. Coefficients were obtained using Propensity Score Reweighting Estimator with sampling weights and bootstrap standard errors. Controls for exporter activity, leverage, foreign ownership status, importer activity, firm age, and computer user share were applied to all models. In the models for labor productivity, we also control for capital stock, intermediate inputs, and the number of employees. In the remaining models we also control for size. The total number of observations is 3,891. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Authors' calculations based on IUTICE, QP and SCIE, INE.

Table 9: First movers versus followers in big data, long-term performance impact

	(1)	(2)	(3)	(4)	(5)
	ΔGVA	ΔTurnover	ΔEmployment	ΔLP	ΔTFP
			Panel A		
Education manager	-0.0021	0.0147	0.0098	-0.0116	-0.0093
	(0.010)	(0.012)	(0.007)	(0.007)	(0.007)
Big data FM adopters	0.1015**	0.0336	0.0211	0.0864**	0.0549*
	(0.045)	(0.049)	(0.036)	(0.041)	(0.033)
			Panel B		
Tenure manager	-0.0088***	-0.0079***	-0.0071***	-0.0012	-0.0003
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Big data FM adopters	0.0932**	0.0263	0.0145	0.0845**	0.0544
	(0.045)	(0.049)	(0.036)	(0.041)	(0.033)
			Panel C		
Prev. manager exper	0.0255	0.0269	0.0143	0.0136	0.0028
	(0.019)	(0.019)	(0.014)	(0.012)	(0.009)
Big data FM adopters	0.1007**	0.0330	0.0208	0.0845**	0.0546*
	(0.045)	(0.049)	(0.037)	(0.041)	(0.033)
			Panel D		
Education workers	0.0311**	0.0085	0.0182	0.0160	0.0116
	(0.015)	(0.013)	(0.011)	(0.011)	(0.010)
Big data FM adopters	0.1019**	0.0339	0.0214	0.0842**	0.0549*
	(0.045)	(0.049)	(0.036)	(0.041)	(0.033)

Notes: All dependent variables are in logs. LP stands for labor productivity. TFP stands for total factor productivity. The coefficients were obtained using long differences model 2015-2019 with Propensity Score Reweighted Estimator. Sampling weights were used. Controls for exporter activity, leverage, foreign ownership status, importer activity, firm age, and computer user share were applied to all models. In the models for labor productivity, we also account for capital stock, intermediate inputs, and the number of employees, as well as size in the remaining models. Robust standard errors are in parenthesis. The total number of observations is 773. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Authors' calculations based on IUTICE, QP and SCIE, INE.

6 Conclusion

This study sheds light on the characteristics of firms that adopt digital technologies and on its impact on firm performance. By categorizing digital adopters into first movers, followers and non-adopters, with a specific focus on cloud computing and big data technologies, we have gained valuable insights into the dynamics of technology adoption and its effects.

We find that first movers in the adoption of cloud computing and big data technologies experience significant positive impacts on various performance measures, when compared to non-adopters, demonstrating the tangible benefits of being at the forefront of technological advancements. Additionally, the impact of big data adoption is influenced by both managerial and workforce characteristics. Specifically, we emphasize the significance of having managers with higher levels of education and less tenure to amplify the performance benefits that big data technology can offer.

Consistent with existing research, our study shows that firms adopting digitalization are typically larger, younger, and employ a higher proportion of highly educated workers and managers, reinforcing the inherent advantages of technology adopters in terms of firm size and the characteristics of human capital.

Furthermore, the study reveals that the education level of managers positively influences the likelihood of digitalization, while managers' tenure has the opposite effect. Past experience of the management team plays a significant role in the probability of being a follower, highlighting the cultural and long-term decision-making nature of early technology adoption. This underscores the importance of intangible assets and human capital skills in the technology adoption process.

This paper also contributes to the current literature by exploring the significance of digital technology characteristics in differentiating the effects of adoption on firm' performance. In the case of the less complex digital technology, cloud computing, our research reveals that managerial characteristics do not play a complementary role in the impact of digitalization on firm performance. Moreover, we have observed that first movers in cloud computing do not experience significantly greater performance gains compared to followers. Conversely, when exploring a more complex digital technology, big data, which requires higher knowledge and preparation, our study concludes that managerial characteristics play a complementary role, amplifying the positive effects of technology adoption on firm performance. Additionally, we have identified an edge for first movers when compared to follower adopters of big data.

While the study acknowledges some limitations due to the constraints of limited datasets tracking technology utilization by firms, it emphasizes the need for robust data collection efforts to explore different time trends in technological impacts and compare effects among various technologies.

Government institutions should prioritize the development of comprehensive datasets on technological adoption to support informed policy-making and foster further technological progress. Understanding the impacts of rapid technology dissemination on labor market dynamics and competition is vital for policymakers to ensure a balanced and inclusive technological landscape that benefits society as a whole.

In conclusion, this study provides crucial insights for businesses, policymakers, and researchers by deepening our understanding of the characteristics of technological adopters and the impacts of technology adoption on firm performance. By recognizing the advantages of first movers, the significance of complementary managerial and employee characteristics, and the varied effects of different technologies, we can pave the way for more informed decisions and policies that promote technological advancements and foster inclusive economic growth.

References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2014). Return of the solow paradox? IT, productivity, and employment in us manufacturing. *American Economic Review*, 104(5):394–399.

Acemoglu, D., Koster, H. R. A., and Ozgen, C. (2023). Robots and workers: Evidence from the Netherlands. NBER Working Paper No. 31009.

Ackerberg, D. A., Caves, K., and Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, 83(6):2411–2451.

Alexandre, F., Cruz, S., and Portela, M. (2021). Financial distress and the role of management in micro and small-sized firms. OECD Productivity Working Papers, No. 2, OECD Publishing, Paris.

Amador, J. and Silva, C. (2023). The impact of ICT adoption on productivity: Evidence from Portuguese firm-level data. Working Papers No. 072023, Banco de Portugal.

Andrews, D., Criscuolo, C., and Gal, P. N. (2015). Frontier firms, technology diffusion and public policy: Micro evidence from OECD countries. OECD Productivity Working Papers, No. 2, OECD Publishing, Paris.

Andrews, D., Criscuolo, C., and Gal, P. N. (2016). The best versus the rest: the global productivity slowdown, divergence across firms and the role of public policy. OECD Productivity Working Papers, No. 5, OECD Publishing, Paris.

Audretsch, D. B. and Belitski, M. (2020). The role of R&D and knowledge spillovers in innovation and productivity. *European Economic Review*, 123:103391.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., and 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.

Ballestar, M. T., Díaz-Chao, Á., Sainz, J., and Torrent-Sellens, J. (2020). Knowledge, robots and productivity in SMEs: Explaining the second digital wave. *Journal of Business Research*, 108:119–131.

Barbosa, N. and Faria, A. P. (2022). Digital adoption and productivity: understanding micro drivers of the aggregate effect. GEE Working Paper No. 0162.

Bartel, A., Ichniowski, C., and Shaw, K. (2007). How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement, and worker skills. *The Quarterly Journal of Economics*, 122(4):1721–1758.

Bartelsman, E. J. et al. (2013). ICT, reallocation and productivity. Economic Papers, No. 486, European Commission.

Berlingieri, G., Calligaris, S., Criscuolo, C., and Verlhac, R. (2020). Laggard firms, technology diffusion and its structural and policy determinants. OECD Science, Technology and Industry Policy Papers, No. 86, OECD Publishing, Paris.

Bloom, N., Brynjolfsson, E., Foster, L., Jarmin, R., Patnaik, M., Saporta-Eksten, I., and Van Reenen, J. (2019). What drives differences in management practices? *American Economic Review*, 109(5):1648–83.

Bloom, N., Eifert, B., Mahajan, A., McKenzie, D., and Roberts, J. (2012). Does management matter? Evidence from India. *The Quarterly Journal of Economics*, 128(1):1–51.

Bloom, N. and Reenen, J. V. (2011). *Human Resource Management and Productivity.* Handbook of Labor Economics. 4, 1967-1767.

Bloom, N. and Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. *The Quarterly Journal of Economics*, 122(4):1351–1408.

Bresnahan, T. F., Brynjolfsson, E., and Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal of Economics*, 117(1):339–376.

Brynjolfsson, E. and McAfee, A. (2012). Winning the race with ever-smarter machines. *MIT Sloan Management Review*, 53(2):53 – 60.

Brynjolfsson, E. and McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies.* WW Norton & Company.

Brynjolfsson, E., Rock, D., and Syverson, C. (2017). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. NBER Working Paper No. 24001.

Brynjolfsson, E., Rock, D., and Syverson, C. (2021). The productivity j-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*, 13(1):333–72.

Busso, M., DiNardo, J., and McCrary, J. (2014). New evidence on the finite sample properties of propensity score reweighting and matching estimators. *Review of Economics and Statistics*, 96(5):885–897.

Calvino, F., Criscuolo, C., Marcolin, L., and Squicciarini, M. (2018). A taxonomy of digital intensive sectors. OECD Science, Technology and Industry Working Papers, No. 2018/14, OECD Publishing, Paris.

Calvino, F., DeSantis, S., Desnoyers-James, I., Formai, S., Goretti, I., Lombardi, S., Manaresi, F., and Perani, G. (2022). Closing the italian digital gap: The role of skills, intangibles and policies. OECD Science, Technology and Industry Policy Papers, No. 126, OECD Publishing, Paris.

Calvino, F. and Fontanelli, L. (2023). A portrait of AI adopters across countries. OECD Science, Technology and Industry Working Papers, No. 2023/02, OECD Publishing, Paris.

Cameron, A. C. and Trivedi, P. K. (2005). *Microeconometrics: methods and applications*. Cambridge University Press, Cambridge: New York.

Carpenter, M. A. (2002). The implications of strategy and social context for the relationship between top management team heterogeneity and firm performance. *Strategic Management Journal*, 23(3):275–284.

Cette, G., Nevoux, S., and Py, L. (2022). The impact of ICTs and digitalization on productivity and labor share: Evidence from French firms. *Economics of Innovation and New Technology*, 31(8):669–692.

Comin, D. and Mestieri, M. (2014). Technology diffusion: Measurement, causes, and consequences. In *Handbook of Economic Growth*, volume 2, pages 565–622. Elsevier.

Daveri, F. and Parisi, M. L. (2015). Experience, innovation, and productivity: Empirical evidence from Italy's slowdown. *ILR Review*, 68(4):889–915.

Engelstätter, B. (2012). It is not all about performance gains–enterprise software and innovations. *Economics of Innovation and New Technology*, 21(3):223–245.

Gal, P. G., Nicoletti, G., Renault, T., Sorbe, S., and Timiliotis, C. (2019). Digitalisation and productivity: In search of the holy grail – firm-level empirical evidence from eu countries. OECD Economics Department Working Papers, No. 1533, OECD Publishing, Paris.

Garicano, L. (2015). Can slow IT adoption explain productivity slowdown. In *Firm size and organizational change. Presentation to CompNet-ECB Workshop, Madrid*.

Giorcelli, M. (2019). The long-term effects of management and technology transfers. *American Economic Review*, 109(1):121–52.

Guadalupe, M., Kuzmina, O., and Thomas, C. (2012). Innovation and foreign ownership. *American Economic Review*, 102(7):3594–3627.

Hall, B. H., Lotti, F., and Mairesse, J. (2013). Evidence on the impact of R&D and ICT investments on innovation and productivity in Italian firms. *Economics of Innovation and New Technology*, 22(3):300–328.

Heeringa, S. G., West, B. T., and Berglund, P. A. (2017). *Applied survey data analysis (2nd edn.)*. Taylor and Francis, London.

Koch, M., Manuylov, I., and Smolka, M. (2021). Robots and firms. *The Economic Journal*, 131(638):2553–2584.

Niebel, T., Rasel, F., and Viete, S. (2019). BIG data–BIG gains? understanding the link between big data analytics and innovation. *Economics of Innovation and New Technology*, 28(3):296–316.

Schivardi, F. and Schmitz, T. (2019). The IT revolution and southern europe's two lost decades. *Journal of the European Economic Association*, 18(5):2441–2486.

Segarra-Blasco, A., Teruel, M., and Cattaruzzo, S. (2022). Innovation, productivity and learning induced by export across european manufacturing firms. *Economics of Innovation and New Technology*, 31(5):387–415.

Stiroh, K. J. (2002). Information technology and the us productivity revival: What do the industry data say? *American Economic Review*, 92(5):1559–1576.

Stoneman, P. and Kwon, M. J. (1996). Technology adoption and firm profitability. *The Economic Journal*, 106(437):952–962.

Torres, S., Portugal, P., Addison, J. T., and Guimaraes, P. (2018). The sources of wage variation and the direction of assortative matching: Evidence from a three-way high-dimensional fixed effects regression model. *Labour Economics*, 54:47–60.

Wu, T.-H., Ting, P. J. L., Lin, M.-C., and Chang, C.-C. (2022). Corporate ownership and firm performance: a mediating role of innovation efficiency. *Economics of Innovation and New Technology*, 31(4):292–319.

A Appendix

A.1 Enhanced sector-specific descriptive analysis

Table 10: Share of technological adopters by sector (%)

	2014	2016	2017	2018
Panel A: Cloud Computing				
Manufacturing industries	4.8	6.7	10.3	11.2
Electricity, gas, steam and cold air	15.4	27.2	25.2	12.2
Wwater; sanitation, waste management and depollution	26.8	19.0	24.0	30.5
Construction	4.7	5.6	9.8	10.7
Wholesale and retail; car and motorcycle repair	6.0	9.7	9.3	11.7
Transport and storage	5.5	6.3	9.2	16.1
Accommodation and catering activities	6.5	8.7	8.7	9.7
Information and communication services	26.9	36.3	44.3	46.0
Real estate activities	6.5	16.1	15.5	15.1
Consulting, scientific, technical and similar services	9.1	18.0	20.3	25.7
Administrative and support services activities	10.2	17.2	20.5	24.2
Other services: Repair of comput. commun. equip.	14.1	11.2	32.1	34.2
Panel B: Big Data				
Manufacturing industries		7.7		7.4
Electricity, gas, steam and cold air		22.0		20.8
Water; sanitation, waste management and depollution		24.0		20.9
Construction		8.6		5.7
Wholesale and retail; car and motorcycle repair		9.7		7.6
Transport and storage		8.6		18.5
Accommodation and catering activities		13.1		7.0
Information and communication services		21.2		20.6
Real estate activities		8.4		7.5
Consulting, scientific, technical and similar services		7.5		10.5
Administrative and support services activities		13.6		7.7
Other services: Repair of comput. commun. equip.		6.6		11.5

Notes: We report the percentage of adopters of each technology among the groups of firms divided by sectors in the panels A to B. All years of the survey are included. Sampling weights provided by the survey are used in this report. Activity classified in sections C, D E, F, G, H, I, J , M, N and group 951 of section S of the Portuguese Classification of Economic Activities, Revision 3.

Source: Authors' calculations based on IUTICE and SCIE, INE.

Table 11: Distribution of technological adopters by sector (%)

	2014	2016	2017	2018
Panel A: Cloud Computing				
Manufacturing industries	13.4	12.4	16.4	15.3
Electricity, gas, steam and cold air	0.3	0.2	0.2	0.1
Water; sanitation, waste management and depollution	1.6	0.7	0.7	0.8
Construction	8.9	6.4	9.9	9.0
Wholesale and retail; car and motorcycle repair	31.8	32.6	26.1	26.6
Transport and storage	4.8	3.1	4.0	5.8
Accommodation and catering activities	8.2	7.5	6.6	6.4
Information and communication services	9.3	8.9	8.9	8.0
Real estate activities	1.7	3.5	2.9	2.9
Consulting, scientific, technical and similar services	14.4	18.4	18.0	18.6
Administrative and support services activities	5.6	6.1	6.0	6.3
Other services: Repair of comput. commun. equip.	0.1	0.2	0.2	0.2
Panel B: Big Data				
Manufacturing industries		15.3		17.1
Electricity, gas, steam and cold air		0.2		0.2
Water; sanitation, waste management and depollution		1.0		0.9
Construction		10.5		8.2
Wholesale and retail; car and motorcycle repair		35.2		29.3
Transport and storage		4.6		11.3
Accommodation and catering activities		12.2		7.9
Information and communication services		5.6		6.1
Real estate activities		2.0		2.4
Consulting, scientific, technical and similar services		8.2		12.9
Administrative and support services activities		5.2		3.4
Other services: Repair of comput. commun. equip.		0.1		0.1

Notes: We report the distribution of adopters of each technology among sectors in the panels A to B. All years of the survey are included. Sampling weights provided by the survey are used in this report. Activity classified in sections C, D E, F, G, H, I, J , M, N and group 951 of section S of the Portuguese Classification of Economic Activities, Revision 3.
Source: Authors' calculations based on IUTICE and SCIE, INE.

Table 12: Distribution of technological cloud computing by main sector (%)

Subsector	Share
Wholesale and retail, car and motorcycle repair	
Sale, maintenance and repair of motor vehicles and motorcycles	17.28
Wholesale (including agents), except of motor vehicles and motorcycles	48.10
Retail trade, except of motor vehicles and motorcycles	34.62

Notes: Sampling weights provided by the survey are used in this report.
Source: Authors' calculations based on IUTICE and SCIE, INE.

Table 13: Distribution of technological big data by main sector (%)

Subsector	Share
Wholesale and retail, car and motorcycle repair	
Sale, maintenance and repair of motor vehicles and motorcycles	15.47
Wholesale (including agents), except of motor vehicles and motorcycles	28.75
Retail trade, except of motor vehicles and motorcycles	55.78

Notes: Sampling weights provided by the survey are used in this report.

Source: Authors' calculations based on IUTICE and SCIE, INE.

Table 14: First movers versus non-adopters, the impact of cloud computing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	GVA		Turnover		Employment		LP		TFP	
Panel A										
Educ manager$_{t-1}$	-0.0005	-0.0003	-0.0013***	-0.0011***	-0.0006*	-0.0005	0.0000	0.0002	0.0002	0.0003*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cloud computing FM$_{t-1}$	0.1474***	0.1785***	0.1004***	0.1269***	0.0862***	0.0951***	0.0777***	0.1084***	0.0378***	0.0749**
	(0.007)	(0.038)	(0.007)	(0.036)	(0.004)	(0.017)	(0.006)	(0.034)	(0.006)	(0.036)
CC$_{t-1}$ × EM$_{t-1}$		-0.0025		-0.0021		-0.0007		-0.0025		-0.0030
		(0.003)		(0.002)		(0.001)		(0.002)		(0.003)
Panel B										
Tenure manager$_{t-1}$	0.0004**	0.0004***	-0.0001	-0.0001	0.0003***	0.0003***	0.0003**	0.0003**	-0.0001	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cloud computing FM$_{t-1}$	0.1473***	0.1520***	0.0990***	0.1056***	0.0860***	0.0820***	0.0780***	0.0814***	0.0378***	0.0419***
	(0.007)	(0.010)	(0.007)	(0.007)	(0.004)	(0.006)	(0.006)	(0.009)	(0.006)	(0.008)
CC$_{t-1}$ × TM$_{t-1}$		-0.0004		-0.0006		0.0003		-0.0003		-0.0004
		(0.001)		(0.001)		(0.000)		(0.000)		(0.000)
Panel C										
Prev manager exper$_{t-1}$	-0.0013	-0.0007	0.0009	0.0016	-0.0008	-0.0009	-0.0022	-0.0020	-0.0002	0.0005
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)
Cloud computing FM$_{t-1}$	0.1470***	0.1491***	0.0991***	0.1016***	0.0857***	0.0851***	0.0777***	0.0785***	0.0379***	0.0403***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
CC$_{t-1}$ × PME$_{t-1}$		-0.0063		-0.0070		0.0020		-0.0023		-0.0068
		(0.006)		(0.007)		(0.002)		(0.004)		(0.004)
Panel D										
Educ workers$_{t-1}$	-0.0012*	-0.0015**	-0.0017**	-0.0017**	-0.0009*	-0.0009*	-0.0008*	-0.0010**	-0.0007***	-0.0009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Cloud computing FM$_{t-1}$	0.1478***	0.1164***	0.1005***	0.1005***	0.0865***	0.0849***	0.0783***	0.0557***	0.0385***	0.0123
	(0.007)	(0.014)	(0.007)	(0.007)	(0.004)	(0.009)	(0.006)	(0.011)	(0.006)	(0.010)
CC$_{t-1}$ × EW$_{t-1}$		0.0029**				0.0001		0.0021**		0.0024**
		(0.001)				(0.001)		(0.001)		(0.001)

Notes: All dependent variables are in logs. LP stands for labor productivity. TFP stands for total factor productivity. Sampling weights were used. Controls for exporter activity, leverage, foreign ownership status, importer activity, firm age, and computer user share were applied to all models. In the models for labor productivity, we also account for capital stock, intermediate inputs, and the number of employees, as well as size in the remaining models. Bootstrap standard errors were used. The total number of observations is 3,366. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Authors' calculations based on IUTICE, QP and SCIE, INE.

A.2 Results Before Propensity Score

Table 15: First movers versus followers in cloud computing, long-term performance impact

	(1)	(2)	(3)	(4)	(5)
	ΔGVA	ΔTurnover	ΔEmployment	ΔLP	ΔTFP
			Panel A		
Education manager	0.0406***	0.0375**	0.0194	0.0164	0.0096
	(0.016)	(0.019)	(0.014)	(0.011)	(0.009)
CC FM adopters	-0.2221**	-0.3107**	-0.1282	-0.0750	-0.0718
	(0.094)	(0.124)	(0.080)	(0.082)	(0.057)
			Panel B		
Tenure manager	-0.0208***	-0.0141**	-0.0155***	-0.0034	-0.0023
	(0.006)	(0.007)	(0.005)	(0.004)	(0.004)
CC FM adopters	-0.2369**	-0.3207***	-0.1444*	-0.0728	-0.0734
	(0.094)	(0.122)	(0.078)	(0.082)	(0.056)
			Panel C		
Prev. manager exper	0.0392	0.0427	0.0386	-0.0049	0.0273
	(0.044)	(0.034)	(0.033)	(0.031)	(0.026)
CC FM adopters	-0.2170**	-0.3051**	-0.1226	-0.0741	-0.0683
	(0.097)	(0.121)	(0.082)	(0.081)	(0.057)
			Panel D		
Education workers	0.0158	0.0202	0.0211	-0.0076	0.0066
	(0.026)	(0.022)	(0.022)	(0.016)	(0.012)
CC FM adopters	-0.2167**	-0.3038**	-0.1212	-0.0751	-0.0696
	(0.093)	(0.118)	(0.078)	(0.080)	(0.056)

Notes: All dependent variables are in logs. LP stands for labor productivity. TFP stands for total factor productivity. The coefficients were obtained using Long Differences Model 2013-2019. Sampling weights were used. Controls for exporter activity, leverage, foreign ownership status, importer activity, firm age, and computer user share were applied to all models. In the models for labor productivity, we also account for capital stock, intermediate inputs, and the number of employees, as well as size in the remaining models. Robust standard errors are in parenthesis. The total number of observations is 909. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Authors' calculations based on IUTICE, QP and SCIE, INE.

Table 16: First movers versus non-adopters, the impact of big data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	GVA		Turnover		Employment		LP		TFP	
Panel A										
Educ manager$_{t-1}$	0.0016***	0.0016***	0.0004*	0.0005*	0.0003	0.0005**	0.0010***	0.0009***	0.0009***	0.0007**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Big data FM$_{t-1}$	0.1268***	0.1335***	0.0866***	0.0959***	0.0751***	0.0952***	0.0655***	0.0603***	0.0295***	0.0090
	(0.003)	(0.010)	(0.003)	(0.010)	(0.003)	(0.006)	(0.002)	(0.006)	(0.004)	(0.007)
BD$_{t-1}$ × EM$_{t-1}$		-0.0006		-0.0008		-0.0017***		0.0004		0.0017***
		(0.001)		(0.001)		(0.000)		(0.001)		(0.001)
Panel B										
Tenure manager$_{t-1}$	-0.0002	-0.0002	-0.0001	-0.0001	-0.0000	-0.0001	-0.0002*	-0.0002	-0.0001	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Big data FM$_{t-1}$	0.1278***	0.1245***	0.0868***	0.0895***	0.0753***	0.0696***	0.0659***	0.0670***	0.0301***	0.0392***
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)	(0.002)	(0.004)	(0.003)	(0.006)
BD$_{t-1}$ × TM$_{t-1}$		0.0003		-0.0002		0.0005		-0.0001		-0.0008**
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Panel C										
Prev manager exper$_{t-1}$	0.0002	0.0003	0.0009	0.0009	0.0006	0.0006	-0.0006	-0.0006	-0.0009*	-0.0012**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Big data FM$_{t-1}$	0.1280***	0.1282***	0.0868***	0.0870***	0.0752***	0.0755***	0.0662***	0.0660***	0.0304***	0.0287***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
BD$_{t-1}$ × PME$_{t-1}$		-0.0002		-0.0002		-0.0004		0.0003		0.0025
		(0.001)		(0.001)		(0.001)		(0.001)		(0.002)
Panel D										
Educ workers$_{t-1}$	0.0019***	0.0021***	-0.0001	0.0000	0.0002	0.0003	0.0015***	0.0015***	0.0011**	0.0009**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Big data FM$_{t-1}$	0.1278***	0.1422***	0.0870***	0.0988***	0.0753***	0.0807***	0.0660***	0.0656***	0.0301***	0.0197**
	(0.003)	(0.009)	(0.003)	(0.006)	(0.003)	(0.007)	(0.002)	(0.009)	(0.003)	(0.010)
BD$_{t-1}$ × EW$_{t-1}$		-0.0014		-0.0012*		-0.0005		0.0000		0.0010
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)

Notes: All dependent variables are in logs. LP stands for labor productivity. TFP stands for total factor productivity. Sampling weights were used. Controls for exporter activity, leverage, foreign ownership status, importer activity, firm age, and computer user share were applied to all models. In the models for labor productivity, we also account for capital stock, intermediate inputs, and the number of employees, as well as size in the remaining models. Bootstrap standard errors were used. The total number of observations is 3,891. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Authors' calculations based on IUTICE, QP and SCIE, INE.

Table 17: First movers versus followers in big data, long-term performance impact

	(1)	(2)	(3)	(4)	(5)
	ΔGVA	ΔTurnover	ΔEmployment	ΔLP	ΔTFP
			Panel A		
Education manager	-0.0338**	-0.0083	-0.0059	-0.0300***	-0.0175
	(0.015)	(0.010)	(0.007)	(0.011)	(0.014)
Big data FM adopters	0.1174*	0.1135*	0.0188	0.1925***	0.0227
	(0.060)	(0.069)	(0.047)	(0.054)	(0.042)
			Panel B		
Tenure manager	-0.0026	-0.0124**	-0.0094***	0.0073*	0.0061
	(0.005)	(0.005)	(0.003)	(0.004)	(0.005)
Big data FM adopters	0.0853	0.0641	-0.0248	0.1837***	0.0323
	(0.055)	(0.055)	(0.042)	(0.056)	(0.046)
			Panel C		
Prev. manager exper	-0.0104	0.0285	-0.0037	-0.0092	-0.0048
	(0.045)	(0.048)	(0.037)	(0.015)	(0.013)
Big data FM adopters	0.0942*	0.1084*	0.0149	0.1658***	0.0107
	(0.056)	(0.065)	(0.046)	(0.054)	(0.046)
			Panel D		
Education workers	0.0232	0.0116	0.0254**	-0.0064	-0.0182
	(0.021)	(0.021)	(0.012)	(0.018)	(0.020)
Big data FM adopters	0.0936*	0.1074	0.0121	0.1684***	0.0114
	(0.055)	(0.066)	(0.043)	(0.054)	(0.045)

Notes: All dependent variables are in logs. LP stands for labor productivity. TFP stands for total factor productivity. The coefficients were obtained using Long Differences Model 2015-2019. Sampling weights were used. Controls for exporter activity, leverage, foreign ownership status, importer activity, firm age, and computer user share were applied to all models. In the models for labor productivity, we also account for capital stock, intermediate inputs, and the number of employees, as well as size in the remaining models. Robust standard errors are in parenthesis. The total number of observations is 773. Significance levels: ***, 1%; **, 5%; *, 10%.

Source: Authors' calculations based on IUTICE, QP and SCIE, INE.

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