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Abstract[1]

The diffusion of medium and advanced digital information and communication technologies (ICTs)—such as e-commerce, websites, cloud computing, and artificial intelligence—has progressed at a rapid pace. However, this diffusion has been uneven across countries, as well as across firms of different ages, sizes, and sectors within countries. In Latin America, this issue is compounded by the lack of firm-level data, which has limited our understanding of how these technologies are being adopted. Using firm-level data provided by the national statistical offices of Chile, Colombia, and Ecuador, we analyze the stylized facts of adoption of cloud computing and artificial intelligence across firm size, age, and sector groups. We examine whether the factors associated with technology adoption in advanced economies also apply in this regional context. Our findings indicate that many of the determinants identified in studies of European and U.S. firms—such as firm size, human capital, and access to complementary resources—are similarly relevant in Latin America. Larger firms, those with higher levels of human capital, and those with access to enabling conditions tend to be earlier and more consistent adopters of digital technologies. Finally, we analyze how the use of cloud computing and AI adoption relate to firm performance. For cloud computing, we find a positive and statistically significant effect across all three economic sectors—manufacturing, retail and wholesale, and services—as well as in all four countries considered. However, for Chilean firms in the manufacturing, retail, and wholesale sectors, the effect is not statistically significant. In the case of AI adoption, Colombian firms experience a positive impact on sales. Nevertheless, this effect loses statistical significance once we implement a two-step procedure that plausibly accounts for endogeneity.

JEL classifications: L25, M12, O14, O31, O33

Keywords: Digital technology, E-commerce, Cloud computing, Artificial intelligence, Productivity

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1. Introduction

The emergence of disruptive technologies, such as artificial intelligence (AI), big data, and cloud computing, generates significant changes in the economy and society, and, very importantly, in how companies conduct their production and innovation processes and manage organizational change (Agrawal et al., 2019). Those disruptive changes impact firms in economies characterized by high informal labor, a lack of innovation, low investment in R&D, and a lack of quality certification in both product and process. Most importantly, they face significant barriers to adopting digital technologies. In addition, emerging economies in the LATAM region have exhibited negative total factors and labor productivity in the last two decades (Seffino and Gonzalez, 2025). In this context, the diffusion of digital technologies and the diffusion of AI, among other disruptive digital technologies, are expected to bring an opportunity to close productivity gap and increase economic opportunities in this region (Agrawal et al., 2019).

The diffusion of advanced digital technologies—such as artificial intelligence, big data analytics, cloud computing, and related tools—has often been preceded by the adoption of medium-level digital communication technologies. These include the use of e-commerce platforms, corporate websites, social networks for business purposes, and high-speed broadband connectivity. Prior research suggests that firms transitioning through these earlier stages of digital adoption are more likely to embrace more advanced technologies later (Zolas et al., 2021; Jung and Gómez-Bengoechea, 2025).

Despite a growing interest in digital transformation, empirical research on the diffusion of advanced technologies across firms in Latin American economies remains limited. Cross-country evidence is particularly scarce concerning the characteristics of firms that adopt medium-level digital technologies, the factors influencing their diffusion, and the extent to which these technologies contribute to improvements in firm productivity.

The first objective of this study aims to examine the process of technological diffusion of two of those disruptive technologies, cloud computing and artificial intelligence, among firms in three Latin American countries: Chile, Colombia, and Ecuador. Specifically, we document the use of those technologies, investigate the role of key enabling factors in shaping this diffusion, and assess the extent to which the adoption of such technologies is associated with firm performance.

To conduct this analysis, we draw on three distinct firm-level surveys, each varying in temporal coverage and survey design. Two of these surveys include a brief module on information and communication technologies (ICT), while one—Colombia's ICT survey—is a specialized and dedicated instrument. Across the countries, available data also cover the use of medium digital technologies, like e-commerce, websites, and social media platforms. More importantly, information on cloud computing adoption is available for three countries, while Colombia's ICT survey provides data on firms' use of artificial intelligence (AI) for the years 2019 and 2020.

The analysis reveals several key stylized facts regarding the adoption of these technologies. First, there is substantial variation in the adoption of these two digital technologies across countries, firm sizes, age groups, and sectors. Second, the technologies of cloud computing and AI are significantly more prevalent among larger firms (consistent with Acemoglu et al., 2023). Third, when examining firms by age group—categorized as young, established, and old—the adoption of these technologies generally increases with the age of the firm. An exception to this pattern is observed with the use of artificial intelligence (AI), where younger firms in Colombia exhibit adoption rates similar to or higher than those of their older counterparts.

Fourth, a closer examination of AI adoption by Colombian firms reveals a heterogeneous diffusion pattern across economic sectors. Notably, the adoption of AI has been significantly more prevalent in the service sector than in manufacturing or commerce.

Fifth, regarding the factors associated with the adoption of digital technologies, complementary ICT-related variables emerge as the most influential—although their impact varies by sector (manufacturing, retail and wholesale, and services). Key drivers include employee training in ICT, access to high-speed broadband connections (over 100 Mbps), the use of social networks, the intensity of digital infrastructure use (such as intranets, extranets, and LANs), and the adoption of specialized management software (e.g., ERP, CRM, SCM). Building on the rich insights of Dahlke et al. (2024) regarding the importance of epidemic or spillover effects, this factor is more crucial in determining the adoption of digital technologies across some sectors. Additionally, the availability of skilled human capital within firms plays a relatively important role.

Sixth, factors such as foreign ownership and export orientation—which might be expected to influence adoption—were, in some cases, not statistically significant. Finally, larger firms were more likely to adopt medium and advanced digital technologies, although this effect was observed only in a limited number of country-sector combinations. Firm age, by contrast, did not appear to be a significant determinant of technology adoption.

The second objective of this study is to assess the relationship of the key digital technologies—cloud computing and artificial intelligence (AI)—on firm performance, as measured by sales and labor productivity. To estimate the potential effects of digital adoption, we employ a reduced-form econometric model based on an augmented Cobb-Douglas production function. When using sales as a performance metric, we extend the standard specification (which includes proxies for labor, capital, and inputs) by incorporating variables that capture the use of either cloud computing or artificial intelligence.

However, this specification may be subject to endogeneity. On the one hand, digital adoption can drive higher sales; on the other hand, firms with greater sales may find it easier to absorb the costs of adopting digital technologies, thereby increasing their adoption. To address this concern, we apply an instrumental variables (IV) approach using a basic instrument to identify causal effects. Plausibly, the instrument is subject to criticisms. Our findings indicate that, in the baseline OLS models, firms in manufacturing, retail, wholesale, and services that adopt cloud computing and AI exhibit a performance premium in both sales and productivity. These positive effects largely remain when addressing endogeneity through the IV-2SLS methodology—particularly for cloud computing among Ecuadorian firms across the manufacturing, retail and wholesale, and service sectors, and for retail and wholesale firms in Colombia. In contrast, while the use of AI shows a positive association with labor productivity in the OLS estimates, the effect becomes statistically insignificant for manufacturing and service firms. It even turns negative for retail and wholesale firms.

This study makes several important contributions to the literature. First, it provides evidence of substantial disparities in the adoption of the two advanced digital technologies across firm sizes and sectors in all three countries analyzed. Second, it underscores the role of key ICT-related complementary factors—not only as drivers of adoption but also as mutually reinforcing elements. Third, the study adds to the relatively limited body of empirical work on the relationship between cloud computing and AI adoption and firm performance in emerging economies, where evidence remains scarce. To date, most empirical research in this area has focused on firms in developed economies, particularly in the United States and Europe.

Micro, small, and medium-sized enterprises (MSMEs) form the backbone of the productive structure in the manufacturing, retail and wholesale, and service sectors across Latin America. The findings that firms adopting these advanced digital technologies are likely to be more productive—

and that complementary factors such as access to fast broadband, employee training in ICT, engagement with digital networks, and the use of specialized management software facilitate adoption—underscore the need for more targeted and proactive policy interventions in areas of training, broadband availability and awareness. These policies should aim to bridge the existing digital gaps and promote inclusive technological diffusion across all firm sizes.

The remainder of the paper is structured as follows. Section 2 reviews the existing literature on the adoption of medium and advanced digital technologies by firms. This section also exposes the conceptual framework of the study. Section 3 details the data sources utilized in this study—namely, the Chilean ELE survey, the Colombian ENTIC survey, and the Ecuadorian ENESEM survey—and presents summary statistics on the adoption of two advanced digital technologies, disaggregated by firm size, age, and sector. In Section 4, we investigate the factors associated with the use of those two digital technologies, focusing on ICT-related complementary factors and conducting the analysis by sector. Section 5 explores the relationship between the use of cloud computing and artificial intelligence (AI) and firm productivity, employing both OLS and a two-step procedure that intends to address potential endogeneity. Finally, Section 6 concludes with a synthesis of the main findings and offers suggestions for future research directions.

2. Literature Review and Conceptual Framework

2.1 Literature Review on the Adoption of Advanced Digital Technologies

After several empirical studies linked the high performance of the US economy in the 1990s to its widespread adoption of information and communication technologies (ICT, referring to a range of technologies used for communication and data processing) (Berman et al., 1994; Morrison and Siegel, 1997; Siegel, 1997; Jorgenson and Stiroh, 2000; Stiroh, 2001; McGuckin and Stiroh, 2002), much has been debated about what factors drive the use of them and what are their effects on firm productivity and profitability (Bresnahan and Trajtenberg, 1995; Brynjolfsson and Hitt, 1996, Acemoglu et al., 2021). The literature on technological changes recognizes the complementary relationship between the adoption and usage of ICT, firm-specific factors, and industrial structure. Since Milgrom and Roberts (1990) pioneered the study on the complementary role of firm-specific operational and organizational characteristics as determinants of the adoption of new information technologies at the firm level, a significant amount of the literature has focused on the identification of the factors that are inherent to varying rates of ICT adoptions across firms Such evidence was primarily obtained from a handful of developed economies, identifying the complementary relationship among the determinants of digital transformation is relevant to countries at all stages of economic development, particularly in emerging and developing economies.

The literature on digital transformation has documented a vast amount of empirical evidence of various factors inherent to a firm's ICT adoption. For instance, the technological diffusion approach mainly focuses on three process aspects. First, from the rank effects perspective, a firm's decision to adopt new technologies may be guided by some firm characteristics that affect its profits and, hence, its incentives to innovate. Second, from the stock effects perspective, early adopters' stock of technologies eventually hurt the expected returns to ICT investments of new adopters, so new potential adopters are likely to refrain from adopting new technologies or adopt them on a smaller scale. Lastly, the adoption of any new technology leads to an order effect, where early adopters obtain higher returns from the technology than later adopters and non-adopters (Karshenas and Stoneman, 1993). Another strand of the literature focuses on the complementarity effects of introducing any new technology with a firm's organizational design and knowledge capabilities (Milgrom and Roberts, 1990, 1995; Caroli and Van Reenen, 2001; Stieglitz and Heine, 2007). In this view, the success of adopting any new technology and its subsequent impact on productivity is determined by the presence of key elements, such as organizational technologies, skills, and innovation efforts. Once correctly introduced into the firm's structure, those elements enable a smooth adoption process of new technologies.

Over the last 30 years, digital technologies have undergone a profound transformation of the world. Firms and households have adapted their productive systems, routines, and consumption patterns to an environment characterized by new tools for transmitting, storing, creating, sharing, and exchanging information. The depth of this process is of such magnitude that it has been compared to past disruptions such as the Industrial Revolution, the deployment of the first transport infrastructures, or the expansion of electric energy. Through the years, technological advances have moved the focus from ICT to broadband Internet and a broader concept of digitalization. Jung and Gómez-Bengoechea (2025) mention that the crucial relevance of this topic is based on the Internet's exponential growth since the second half of the 1990s, on the appearance of more powerful uses for the existing technologies, and on the development of novel ones, such as AI, Big

Data, Cloud Computing, and robotization. These new digital technologies can boost value-added creation, reducing the costs of search, replication, transportation, tracking, and verification (Goldfarb and Tucker, 2017), and favor the emergence of new business models throughout the economy.

The COVID-19 pandemic has accelerated the digital transformation, and social distancing restrictions have forced firms to reorganize their production to effectively use teleworking and online sales and purchase goods and services. This situation has generated a substantial acceleration of firms' digital adoption. However, existing evidence of significant heterogeneity in adoption rates indicates that more substantial increases occur among firms that were already digital (Riom and Valero, 2020; EIB, 2021; McKinsey, 2021; World Bank, 2021; DeStefano, Kneller, and Timmis, 2023). This situation shows that the positive aggregate effect of increased digitalization on productivity may be coupled with a strengthening of pre-existing digital divides, potentially adversely affecting long-term growth. Path dependence on a low adoption rate may hinder new adopters of cutting-edge technologies.

Therefore, the accelerated growth of AI capacities has increased expectations of unprecedented productivity growth after decades of economic stagnation (Filippucci et al., 2024). The literature agrees that AI adoption could increase productivity, but there is no consensus on the levels at which this might occur. For example, Acemoglu (2024) maintains that current AI capacity can only generate moderate increases in productivity at the macro level over the coming decade. Korinek and Suh (2024) identify scenarios of exponential economic growth, primarily based on the effects of AI on innovation and technological progress. Very recently, McElheran et al. (2025) have found a positive lagged effect of the adoption of AI on firms' growth in the United States. However, the availability of data at the firm level on the use of AI by firms has lagged considerably behind, particularly in developing countries; thus, there is scant evidence regarding the degree of AI diffusion and its impact on firms. After conducting an exhaustive review of the AI literature, Raj and Seamans (2019) conclude that aggregated industry or country-level statistics have not facilitated in-depth studies that can characterize firms that adopt AI and the conditions under which AI can impact performance at the firm level.

The scarcity of empirical evidence on the diffusion of AI in the business sphere can be attributed to an asynchrony between the accelerated adoption of these technologies and the capacity of national statistics offices to capture the phenomenon. In recent years, business surveys conducted by national statistics offices have begun to include modules on adopting emerging technologies, including those linked to AI. However, as Calvino and Fontanelli (2023b) point out, these advances are still incipient, especially outside the United States, and we can see that for LATAM countries.

Zolas et al. (2020) conducted a pioneering study to understand the adoption of AI by businesses in the United States. Analyzing the 2018 Annual Business Survey (ABS), they gathered information on the diffusion of advanced technologies among U.S. firms. The study reveals that the adoption of advanced technologies is uncommon and tends to be led by the largest and oldest firms. These adoption patterns are consistent with a hierarchy of growing technological sophistication, where most firms that adopt AI or other advanced technologies also use other, more widely available technologies. Finally, although few firms find themselves on the technological frontier, they tend to be larger, which means that the technological exposure of the average worker is significantly greater. Moreover, although technology adoption is closely associated with a series of observable business characteristics, there is significant heterogeneity concerning adoption, which persists even after controlling for many of these characteristics.

McElheran et al. (2024a) use the ABS and find that nearly 6 percent of U.S. firms use AI-related technology. The manufacturing, information, and healthcare sectors utilize AI extensively, with an adoption rate of approximately 12 percent. Most large firms reported using some form of AI. Among young and dynamic firms, the use of AI is more significant among entrepreneurs with the most training and experience. AI adoption is also more common among new firms that posted indicators of higher growth, such as financing of risk capital and innovation. Their study also reveals that the early adoption of AI is far from uniformly distributed across the market's geographic, sectoral, or age terms. If these early AI use patterns persist, the AI adoption gap will likely widen. More recently, McElheran et al. (2024b), using data from the 2021 Management and Organizational Practices Survey (MOPS), a supplement to the 2021 Annual Survey of Manufacturing (ASM), found that, on average, manufacturing firms in the United States that year were using some form of AI.

Calvino and Fontanelli (2025) analyze the characteristics of French firms that utilize AI by combining data from the 2021 and 2023 French ICT surveys administered by the French Statistical Office with the firms' balance sheets. The results show that 6.2 percent of French firms with more than 10 employees utilize some AI-related technology. The use of AI varies by the firm's age: AIpurchasing firms tend to be older, whereas those that develop in-house AI solutions tend to be younger. At the sector level, the ICTs represent the highest proportion of AI users, especially those that produce them in-house. Calvino and Fontanelli (2024) emphasize the importance of complementary assets in AI adoption, including human capital, the utilization of other digital technologies, access to high-speed broadband, and the prior availability of ICT skills.

Czarnitzki et al. (2023) use microdata from the German contribution to the European Commission's Community Innovation Survey. The information gathered is from 2018 and represents all German firms with at least five employees in the manufacturing and mining sectors, public services, and business-oriented services. Approximately 7 percent of German companies utilize AI. Of these, roughly 60 percent use AI in their products or services, 56 percent in process automation, 34 percent in data analysis, and 22 percent in customer interaction. The firms that use AI are, on average, the largest in terms of employment and sales and report a more accelerated growth rate in sales. Innovative performance is better among firms that adopt AI, as evidenced by higher expenditures on research and development (R&D) per employee and a higher proportion of firms reporting results from innovation.

In contrast to the cases of France, South Korea, and the United States, the study finds no significant differences in the age of firms that use AI compared to those that do not. The diffusion of AI among German firms has progressed rapidly. Licht and Wohlrabe (2024), using data from the IFO business survey for 2023 and 2024, found that by June 2023, 13.3 percent of firms were using AI—nearly double the percentage reported by Czarnitzki et al. (2023). Surprisingly, this figure doubled again in 2024, reaching 27 percent. This trend may reflect a growing awareness among firms of the potential benefits of adopting this disruptive digital technology.

Herrera et al. (2024) analyze various aspects of AI adoption among Colombian manufacturing firms. This is the first study to describe how AI is adopted within firms in a Latin American and Caribbean (LAC) country, the typology of adopting firms and industries, and the regions where they operate. The study's results yield new empirical evidence on the diffusion of AI among firms in middle-income countries, helping to close the knowledge gap regarding the characteristics of AI adoption at the global level. Understanding the factors associated with the use of AI and other advanced digital technologies will enable us to comprehend the role of AI adoption in promoting productivity across various economic sectors.

Regarding the relationship between the use of advanced digital technologies and firms' performance, some studies have examined the impact of cloud computing and artificial intelligence on firm performance, drawing on firm-level data. Notable contributions include those by Chen, Guo, and Shangguan (2022); Czarnitzki, Fernández, and Rammer (2023); DeStefano et al. (2023); Calvino and Fontanelli (2023); Conti, Godinho de Matos, and Valentini (2024);[2] Duso and Schiersch (2025); and McElheran et al. (2025). These works collectively highlight the growing relevance of advanced digital technologies like cloud computing and AI adoption in shaping firm-level outcomes and underscore the importance of firm-specific factors in mediating the effects of digital transformation.

Several recent studies have examined the impact of cloud computing on firm performance using firm-level data. Notably, Chen et al. (2022), DeStefano et al. (2023), and Duso and Schiersch (2025) examine the impact of cloud adoption on various performance indicators. Chen et al. (2022) investigate the effects of cloud computing adoption on multiple firm performance metrics. Their findings suggest that firms adopting cloud technologies experience significant gains in profitability and market value, as measured by return on assets (ROA). The study also emphasizes the moderating roles of industry type and firm size in shaping these outcomes. Specifically, manufacturing firms experience greater improvements in profitability after adoption, while the market value effects are more pronounced among service-sector firms. Furthermore, small firms exhibit larger profitability gains following adoption, whereas larger firms benefit more in terms of market valuation.

DeStefano et al. (2023) analyze a rich dataset of UK firms that includes detailed information on the use of seven distinct types of cloud computing technologies. Employing a model like equation (3) below, the authors test their central hypothesis: that the impact of cloud technology adoption differs between young and mature firms. To address endogeneity concerns, they implement an instrumental variable (IV) strategy using granular data on fiber infrastructure, including i) initial access to fiber broadband (lagged by one period) and ii) a detailed regional indicator of fiber deployment. Their findings reveal positive effects of cloud adoption on

[2] Conti et al. (2024) examine the impact of adopting Big Data analytics on firm performance, specifically investigating whether the effects differ across two key performance metrics: value added and revenue. Using a production function framework augmented with the Big Data analytics technology, the authors find that Big Data adoption has a positive effect on both value added and revenues. Notably, the effects are more pronounced for small firms compared to large firms.

employment, sales, and labor productivity for both young and older firms. However, the impact on productivity is not statistically significant.

Duso and Schiersch (2025) assess whether the adoption of cloud computing impacts labor productivity of German firms over the period 2013 to 2016. Like DeStefano et al., they employ a production function framework augmented with cloud computing as an additional input. To address potential self-selection bias in cloud adoption, they use broadband availability at the municipal level as an instrumental variable. Their IV-2SLS regressions reveal that cloud computing yields a labor productivity premium only for firms in the manufacturing sector—particularly large manufacturing firms—and for large firms in the service sector.

Regarding artificial intelligence (AI), several studies—including Czarnitzki, Fernández, and Rammer (2023); Calvino and Fontanelli (2023, 2024); and McElheran et al. (2025)—have investigated the impact of AI adoption on various dimensions of firm performance. Czarnitzki et al. (2023) are among the first studies to examine the relationship between AI usage and productivity empirically. Using a sample of German manufacturing firms, the authors estimate a production function that incorporates standard inputs—labor, capital, and raw materials—following the structure outlined in equation (3) below. They employ three empirical strategies: cross-sectional ordinary least squares (OLS), two-stage least squares (2SLS) with instrumental variables, and entropy balancing. The analysis is based on data from a single year. For the IV approach, they use three instruments: i) the number of firms using AI within each two-digit NACE sector prior to the survey; ii) average annual innovation expenditure per employee, also measured prior to the survey; and iii) survey responses reflecting employee resistance to technology adoption. Across both OLS and IV specifications, their results indicate that AI adoption is positively associated with firm productivity, confirming AI's role as a productivity-enhancing technology.

Calvino et al. (2023) examine the relationship between AI adoption and labor productivity, measured as the ratio of turnover to employees, across nine OECD countries. Their analysis employs a regression specification like equation (3) below, though it excludes capital and material inputs. The authors estimate extended productivity models that incorporate complementary information and communication technology (ICT) factors. Their findings indicate that AI adoption is positively and significantly associated with labor productivity in firms located in Belgium and Denmark. However, no statistically significant association is found for firms in the remaining seven countries: France, Germany, Israel, Italy, Japan, Korea, and Switzerland. The relationship between AI and labor productivity is examined at the country level, given that the datasets differ across the nine countries analyzed. A similar approach is followed in our study, as the datasets for Chile, Ecuador (for cloud computing), and Colombia (for both cloud computing and AI) are distinct, as explained in Section 3.

Using a sample of French firms, Calvino and Fontanelli (2024) investigate the relationship between three measures of AI adoption—AI users, buyers, and developers—and labor productivity. Their model includes lagged explanatory variables such as AI adoption status, IT-related controls, and initial productivity levels. The results indicate a positive association between AI adoption and labor productivity; however, this relationship loses statistical significance once initial productivity and IT controls are considered. The authors interpret this as evidence that more productive firms with stronger digital capabilities are more likely to self-select into AI adoption. Notably, significant effects are observed only for firms that develop AI in-house. To address potential endogeneity, the authors estimate an endogenous treatment regression model. Their findings confirm that only in-house AI development has a statistically significant and positive impact on labor productivity.

To summarize, the empirical evidence on AI adoption is concentrated in high-income countries, where adoption is uneven and dominated by large firms and present in specific sectors. The studies indicate that the size and age of the firm, as well as the presence of other intangible assets, influence the adoption of AI. The empirical evidence on the association of the use of these technologies with firms' performance is mostly positive. In some studies, researchers have found with the use of instruments a causal effect of the adoption of these technologies with sales and labor productivity.

2.2 Conceptual Framework

2.2.1 Digital Technologies

Technological advances over the past decades are crucial to understanding the current concept of digitalization. Before the term "digitalization" became a generalized term, the main body of literature referred to innovations linked to computers and communications as ICT or IT. Baskerville, Myers, and Yoo (2019) explain that IT can be defined as the infrastructure systems necessary to deliver communications services. Gunday et al. (2011) define ICTs as the systems that transmit, store, process, display, create, and automate information dissemination among various technologies, including television, fixed and mobile phones, radio, satellite systems, video, computer software, hardware, and associated equipment and services. This was the main picture up to the mid-1990s.

The massive expansion of the Internet since the mid-1990s has increased the capabilities and services associated with ICT, initially through the development of applications such as email, web searching, and messaging. This process covers up to the first years of the twenty-first century. Since then, the deployment of high-speed broadband Internet networks has triggered a process by which all these different ICT networks converged into a wide range of novel digital tools. More recently, the use of these digital tools for business management has been referred to as digitization, digitalization, or digital transformation (Ross, Beath, and Mocker, 2019; Weill and Woerner, 2018).

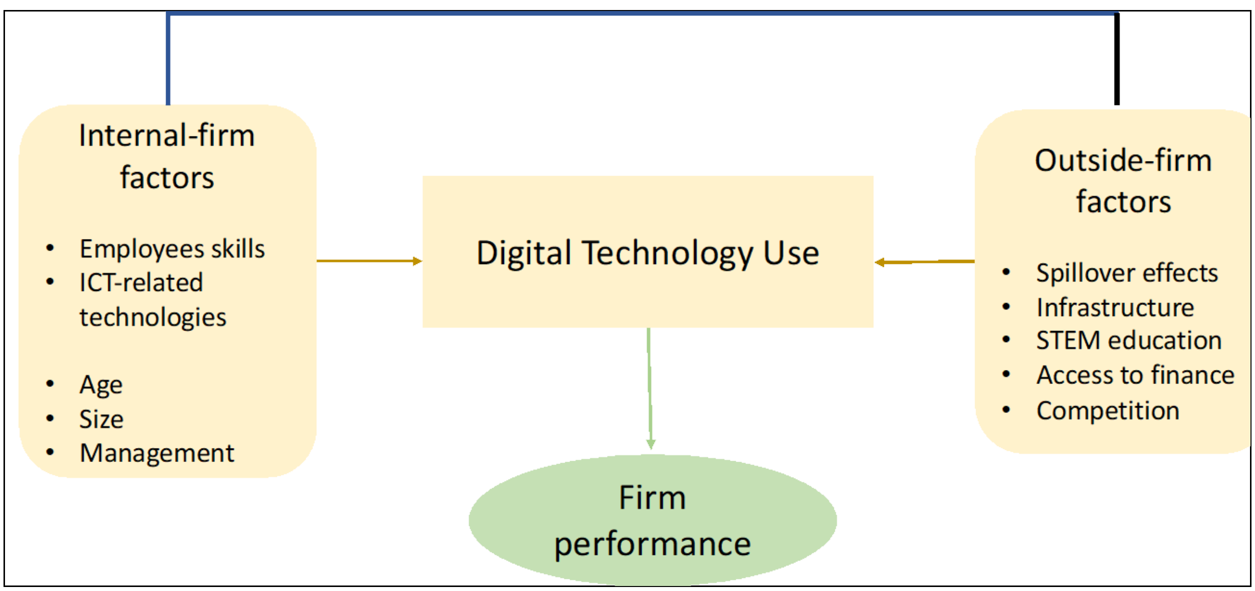
Different definitions of digitalization indicate that the concept can be examined from multiple perspectives. While some authors prefer to take a narrower approach (Brennen and Kreiss, 2016), defining digitalization as the material process of converting analog streams of information into digital bits, others adopt a broader view of digitalization and characterize it as an interactive or symbiotic process with the traditional world. In short, digitalization involves an organization, industry, or country adopting or diffusing digital technologies, which transforms and restructures social and economic conditions around it (Brennen and Kreiss, 2016).

The literature on the adoption of digital technologies has proposed categorizing technologies into two groups based on their level of sophistication: medium and advanced. Medium digital technologies include websites, social networks, e-commerce, and managerial software systems (including several systems depending on the country's context). These tools are adopted and diffused not only by firms but also by individuals. Advanced or cutting-edge technologies are typically employed by medium and large companies, depending on the sector in which the company operates, the skills of its workforce, and the presence of complementary factors. Cloud computing services, AI, big data, IoT, blockchain, and robotics are the most common technologies, as they are machine-based systems that can influence the environment by producing output in response to a given set of objectives. This definition highlights the use of data and other inputs to capture patterns, perform analysis, and formulate outcomes. Big Data offers a solution for increasing firms' reliance on analysis to make better business decisions, understand customers, produce better products, or improve business operations.

2.2.2 Factors Associated with the Use of Digital Technologies

We categorize the factors associated with the use of digital technologies as internal and external to the firms (Calvino et al., 2022), as shown in Figure 1. The first group includes firm characteristics such as sector of activity, firm size, and age, and firm capabilities, including those related to human capital, such as the quality of its workforce and management, and those related to technology, including whether the firm has adopted other (complementary or substitute) technologies or whether complementary intangible assets (like R&D expenditures or intellectual property) are present. The second group focuses on firms' access to broadband infrastructure, foreign technology spillovers arising at the sectoral or geographical level, the quality of the education system and its ability to supply digital skills, and public policies aimed at fostering firm digitalization.

Figure 1. Enablers of Digital Technology Adoption and Performance Gains



Source: Adapted from Calvino et al. (2022) and literature review.

Internal Firm Factors

- **Size and Age**

A firm's age is a proxy for its technological experience, and one of the most tested hypotheses in the literature is that the size of a firm is positively correlated with ICT adoption, with the presumption that larger firms can afford to devote more capital and resources to ICT adoption than smaller ones. For instance, Premkumar and Roberts (1999) and Geroski (2000) suggest that, given the high risks and costs associated with early adoption of ICT, larger firms are better positioned to take the initiative in deploying new technologies.

In a similar context, Cohen and Levin (1989) argue that large firms are more likely to adopt ICT as they are better prepared to absorb the financial burden of sizeable up-front investment expenditures in ICT through economies of scale. In this line of analysis, Acemoglu et al. (2023) find that adopters of AI and robotics are not only predominantly large firms but also those experiencing faster growth. Although a few studies find that the size of firms is either irrelevant or even adverse to firms' ICT investment, the main findings in the literature are in support of a positive correlation between the ICT adoption and the size of firms (Lucchetti and Sterlacchini, 2004; Kinkel, Baumgartner, Cherubini, 2022; Acemoglu et al., 2023; Calvino et al., 2022).Size is associated with fewer financial constraints and lower risk aversion. The metrics used to classify firms according to their size are usually total revenues or the number of employees. Larger companies are presumably in a better position to withstand the costs and risks associated with the introduction of new technologies (Fabiani et al., 2005; Giunta and Trivieri 2007; Haller and Siedschlag 2011; Teo and Tan 1998).

Unlike firm size, the effect of firm age on the adoption of medium and advanced digital technologies is negative. Several studies—including Zolas et al. (2020), Acemoglu et al. (2022), Calvino and Fontanelli (2023), DeStefano (2024), and McElheran et al. (2025)—have found that older firms are generally less likely to adopt technologies such as AI and cloud computing compared to younger firms.

- **Human Capital**

Human capital is generally captured by the percentage of skilled workers (e.g., those with at least a bachelor's degree). A more educated workforce facilitates the early adoption of technologies

(Chun, 2003). Additionally, demand for skilled workers increases with the adoption of new technologies (Bartel & Sicherman, 1999). Other researchers, such as Acemoglu and Restrepo (2020), warn that the current trend is to develop AI in a direction that further automates tasks. This is aimed at replacing labor and substituting it with cheaper capital. Ultimately, the labor share's participation in total value added can be reduced.

A crucial implication of ICT adoption at the firm level is that individual employee traits, such as educational attainment, influence the implementation of new technologies within an organization. As for the educational level of workers, a common proposition in the literature has been that ICT investment and adoption at the firm level can be facilitated when a firm's workforce comprises a relatively large number of highly educated (or high-skilled) workers because ICT usage and its impact on productivity are likely to increase with the number of workers with higher educational attainment. Learning capabilities can be considered complementary inputs to the innovation-adaptation process and production within a firm, as they enable the firm to assimilate new knowledge and facilitate learning efficiently. Such a complementary relationship between the adoption of ICT and the educational level of workers has been evidenced in many studies (Chapman et al., 2000; Bresnahan, Brynjolfsson, Hitt, 2002; Black and Lynch, 2004; Lucchetti and Sterlacchini, 2004; Arvanitis, 2005; Fabiani et al., 2005; Haller and Siedschlag, 2011). Fontanelli et al. (2024) examine the enabling role of human capital in promoting the adoption of predictive AI systems by French firms. Their main finding is that increasing the average share of ICT engineers in firms that do not currently use AI to the level observed in firms that do use AI is associated with higher firm growth.

- **Internal Capabilities**

Another central aspect of the complementarity view in the literature on ICT technology adoption has been the relationship between the adoption of ICT and the organizational characteristics of a firm. The primary reasoning behind organizational complementarity is twofold. First, the adoption of ICT is likely to be facilitated when a firm's decentralized decision-making process and organizational structure consist of fewer hierarchical levels. This result is because productivity gains from ICT adoption are expected to be greater when such a decentralized and delayered organizational structure allows for increased information sharing and more effective involvement in decision-making among employees (Caroli and Van Reenen, 2001; Bresnahan et al., 2002;

Black and Lynch, 2004; Fabiani et al., 2005; Bayo and Lera, 2007; Giuri et al., 2008). Secondly, several studies have focused on a reverse organizational complementarity that runs from the adoption of ICT to organizational changes (Bresnahan and Trajtenberg, 1995; Giuri et al., 2008).

Outside Firm Factors

- **International Engagement/Foreign Trade**

The theory of international engagement suggests that firms participating in foreign trade are more likely to adopt new technologies (Haller and Siedschlag, 2011; Hollenstein, 2004; Lucchetti and Sterlacchini, 2004). Foreign-owned companies tend to be early adopters, contributing to the diffusion of technology in the countries and sectors in which they operate (Keller, 2004; Narula and Zanfei, 2006).

Another interesting aspect of the relationship between the industrial environment and ICT adoption is that firms in international markets are more likely to invest in ICT because they have a strong incentive to reach new customers worldwide via Internet-based technologies. Many empirical studies have evidenced a positive relationship between ICT adoption and the global market (Braga and Willmore, 1991; Hollenstein, 2004; Fabiani et al., 2005).

- **Location Effect (Region)**

Location has also been found to play a significant role in the adoption of digital technology, with urban or densely populated areas facilitating faster uptake. This relationship was first examined by Forman, Goldfarb, and Greenstein (2005) in their study on the diffusion of the Internet. They hypothesized that demand for new technologies increases with city size due to the concentration of information-intensive firms in urban areas. This insight appears even more relevant today, given the complexity and requirements of advanced digital technologies.

- **Sector Effects**

Several studies have also attempted to link industry-specific technological opportunities to the likelihood of ICT adoption at the firm level. For instance, Hollenstein (2004) uses a firm's assessment of the potential to use ICT on a 5-point Likert scale, while Bayo and Lera (2007) and Fabiani et al. (2005) use binary variables to differentiate individual firms across different industries. Regarding the use of advanced digital technologies (AI, cloud computing, big data, for instance), recent research has found a broader use of them in manufacturing, the information sector, professional services, healthcare, retail, and wholesale (Zolas et al., 2020; Acemoglu et al., 2022; McElheran et al., 2024; and McElheran et al. 2025).

The empirical analyses also include control variables for the country and sector in which companies operate. Technology diffusion varies from country to country due to its characteristics, such as size, distance to the technological frontier, domestic absorptive capacity, sectorial specialization, and international integration (Keller, 2004). The economic relevance of a sector or the structural peculiarities of an industry also affect adoption and diffusion. Firms that operate in more digitally advanced environments may face lower costs and higher benefits from technological adoption.

3. Data Sources and Summary Statistics

In this section, we present the study's data, report key summary statistics, and first explore the patterns of digital technology use. Our analysis is based on microdata sources from three countries: Chile, Colombia, and Ecuador.

3.1. Data

The datasets from the surveys used in this research come from *different* methodologies and question structures. Except for the Colombian case, their objectives extend beyond simply providing information about ICT dynamics in the countries under study. Therefore, it is necessary to explain these surveys and the ICT variables that can be extracted from them. In the following subsections, we will provide these explanations.

3.1.1 Chile

For Chile, we use data from the 2013, 2015, and 2017 editions of the Chilean Longitudinal Survey of Companies (*Encuesta Longitudinal de Empresas* – ELE), which is managed by the Chilean Statistical Office (INE). To ensure the representativeness of the longitudinal sample, each wave of the survey includes a fixed panel of firms, along with a complementary longitudinal sample. This complementary sample is used to restore the fixed panel in case of firm non-responses or when a larger sample is required. The ELE has a more significant proportion of medium-large and large firms than the other surveys and includes only a few micro firms.

ELE is not a formal ICT survey but includes an “"ICT Module.” Only the third, fourth, and fifth editions of the seven available ELE editions contain this module. Additionally, the number of ICT-related questions varies across these three editions.

3.1.2 Ecuador

For Ecuador, we use data from the 2016 to 2022 editions of the Ecuadorian Business Structural Survey (*Encuesta Estructural Empresarial* – ENESEM), managed by the Ecuadorian Statistical Office (INEC). ENESEM is an annual survey primarily focused on large and medium-sized companies in the manufacturing, mining, construction, trade, and services sectors. We choose to work with firms in manufacturing, retail and wholesale, and service.

Like ELE, ENESEM is not a formal ICT survey. However, since 2016, every edition has included an “ICT Chapter.” Unlike Chile’s ELE, the number of ICT-related questions in ENESEM has remained consistent.

3.1.3 Colombia

We use four surveys and corresponding datasets for Colombia, all managed by the Colombian Statistical Office (DANE). The primary survey is the Colombian ICT Survey (*Encuesta de Tecnología de la Información y las Comunicaciones*—ENTIC), a specialized survey conducted in 2019 and 2020 on several ICT-related topics.

The other three surveys are the Annual Manufacturing Survey (Encuesta Anual Manufacturera—EAM), the Annual Survey of Retail and Wholesale (Encuesta Anual de Comercio—EAC), and the Annual Survey of Services (Encuesta Anual de Servicios—EAS). We use the 2019 and 2020 versions for these three surveys. Since these are separate surveys, DANE provides a standard identifier for each, allowing researchers to merge the datasets. Questions across these surveys differ.

All surveys target micro, small, medium, and large firms. However, in the three economic sectors covered, including large and medium-large firms is mandatory. The surveys for both years maintain the same number and wording of questions.

Throughout this study, we focus the analysis only on companies from the retail and wholesale, manufacturing, and service sectors in descriptive and econometric exercises.

3.2 Summary Statistics

Table 3.1 presents the distribution of firm-year observations in the samples across economic sectors, firm age, and size groups as a starting point for describing the information reported in the surveys for the four countries.

Significant differences exist in the distribution of firms across manufacturing, retail and wholesale, and services. More firms operate in retail and wholesale in Ecuador, whereas in Colombia, most are in the services sector.

Regarding firm age, the composition of firm-year observations shows a strong bias toward older firms in all four countries. This bias is particularly pronounced in Colombia's manufacturing and retail and wholesale sectors, where young firms are relatively scarce. This pattern suggests low competition or a significant misallocation of resources.

Table 3.1 Distribution of Firms According to Economic Sectors, Age and Size Groups

Category	Ecuador 2016-2022	Chile 2013 - 2017	Colombia (2019-2020) */		
			Manufacturing	Retail and wholesale	Service
Economic sector					
Manufacturing	4950	2693	12721		
Commerce	10714	1608		16257	
Service	7561	3017			25005
Firm age (Years)					
Young [1 - 5]	1693	700	137	198	1449
Established [6 - 10]	3459	1332	657	1783	3857
Old > 10	17102	5286	11927	14276	16699
Size groups (# employees)					
Micro [1-9]	1647		1777	1819	1321
Small [10-49]	7908	1240	6319	7993	7481
Medium [50-249]	9699	1716	3694	5485	9796
Large > 249	3971	4362	931	960	6407

Source: Authors calculation based on Chile ELE, INE; Colombia, ENTIC, EAM, EAS, EAC; Ecuador, ENESEM, INEC */ Different surveys

Additionally, in Chile, the number of micro firms (fewer than 10 employees) was too small, so all firms with fewer than 50 employees were grouped into the small-size category. In this country, large firms outnumber the combined total of small and medium-sized firms. In Ecuador, medium-sized firms comprise the most significant proportion of the sample. Meanwhile, firms with fewer than 250 employees in Colombia constitute the majority.

The distribution of firms by size is likely influenced by the sampling and statistical procedures used in the surveys. Ultimately, firms are highly heterogeneous across these three classifications in the four countries.

3.2.1 Use of Cloud Computing

The adoption of medium and advanced technologies has accelerated due to advancements in computing power, increased internet speed, and, most notably, the rise of cloud-based service models. Cloud computing is a special concept. What is it? Mell and Grance (2011, p. 2), of the NIST (National Institute of Standards and Technology), define “Cloud computing (as) a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction. This cloud model comprises five essential characteristics, three service, and four deployment models.” The NIST also provides a taxonomy of service models that can be offered through cloud computing:

a) Software as a Service (SaaS)
b) Platform as a Service (PaaS)
c) Infrastructure as a Service (IaaS)

The surveys used in this study inquire about using cloud computing differently. The Chilean ELE asks, “What type of software does the firm use?” and includes “cloud computing software” as one of the response options. The Ecuadorian ENESEM asks about the “types of business activities for which the internet is used,” with one option being “utilizing it for cloud services.” The Colombian ENTIC focuses on “methodologies or certifications adopted by the firm,” where one of the possible responses is “cloud computing.”

While the wordings and scope of the questions vary across surveys, we loosely interpret all three as referring to cloud computing. Additionally, the reported use of management-related technologies (such as ERP or CRM systems) likely reflects the adoption of Software as a Service (SaaS), particularly in Ecuador and Chile.

Figure 3.1a Cloud Computing Use across Countries by Size Groups: Manufacturing

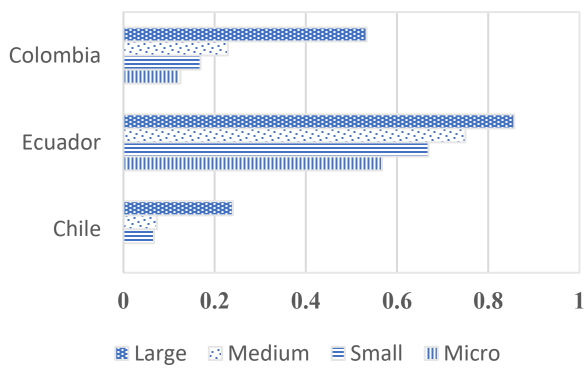


Figure 3.1b Cloud Computing Use across Countries by Age Groups: Manufacturing

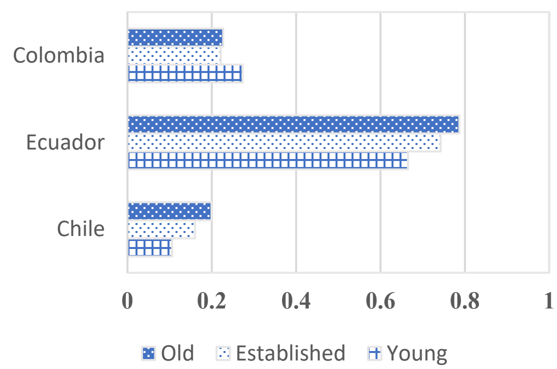


Figure 3.1c Share of Firms Using Cloud Computing across Countries by Size Groups: Retail and Wholesale

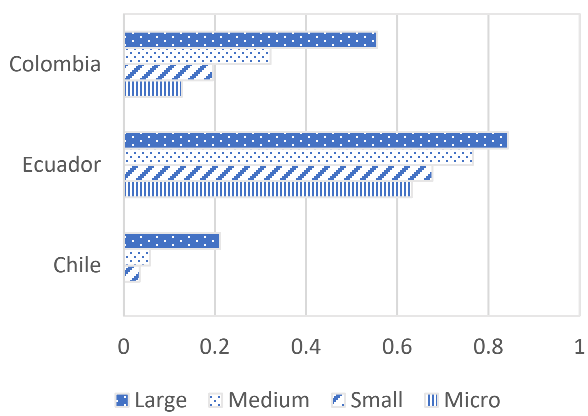


Figure 3.1d Share of Firms using Cloud Computing across Countries by Age Groups: Retail and Wholesale

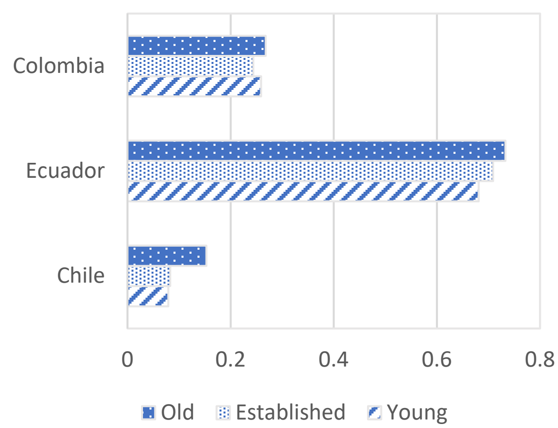


Figure 3.1e Share of Firms Using Cloud Computing across Countries by Size Groups: Service

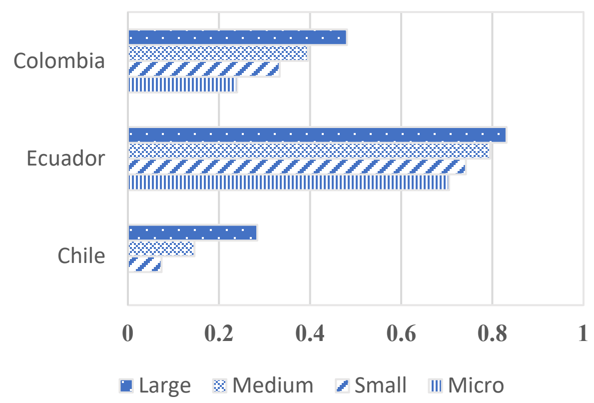
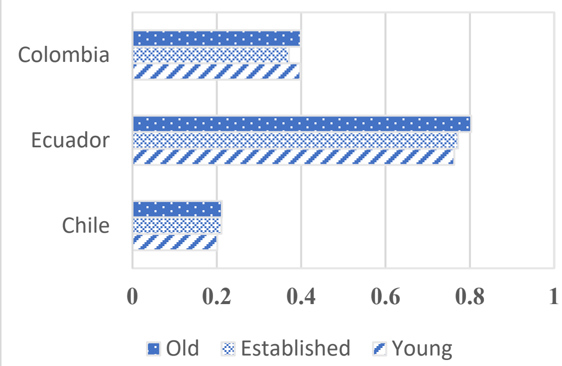


Figure 3.1e Share of Firms Using Cloud Computing across Countries by Age Groups: Service



Source: Authors' calculations based on ELE-INE; ENESEM-INEC; EEA-INEI; ENTIC-Dane.

Figures 3.1a to 3.1e present the average use of cloud computing reported by firms in Chile, Ecuador, and Colombia—some facts to comment on. First, large firms use cloud computing more than firms of other sizes in the three countries. Second, firms' average use of this technology is surprisingly very high in Ecuador compared to firms in Chile and Colombia. A similar trend is reported by Caldarola and Fontanelli (2024) and the OECD.

According to the OECD, Finland had the highest rate of cloud computing adoption among European countries in 2023, with 78.3 percent of firms using the technology—up from 56.9 percent in 2016. In contrast, Turkey had the lowest adoption rate, with only 16.4 percent of firms using cloud computing in 2023, compared to 10.3 percent in 2016.[3]

When comparing Latin American countries with their European counterparts, a noticeable gap remains with leading adopters like Finland and Sweden. However, Latin America surpasses several other European countries, including Turkey, Greece, and even France, in terms of *average* cloud computing adoption.

3.2.2 Use of AI by Colombian Firms

The Colombian ENTIC survey includes a dedicated section on using artificial intelligence (AI). Two specific questions address whether firms use AI technologies either in-house or through third-party providers. We construct a binary (dummy) variable that takes a value of one if a firm reports

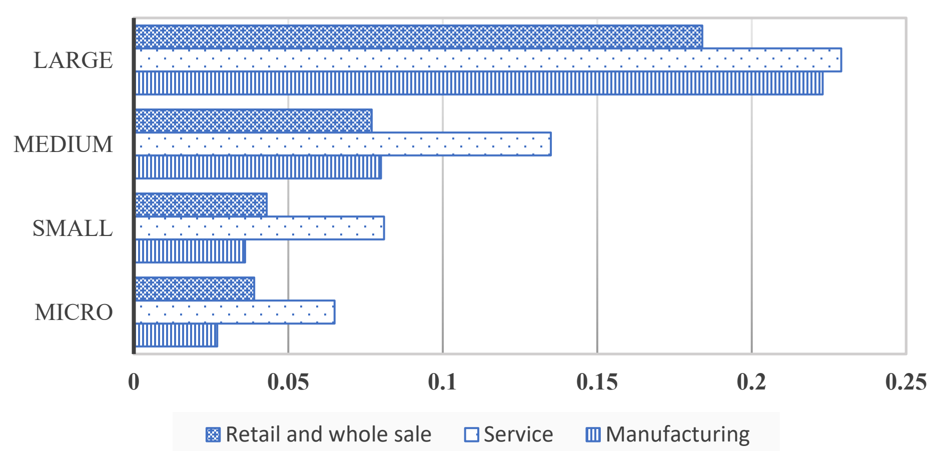
[3] Available at https://goingdigital.oecd.org/en/indicator/25

using AI in either form. Figures 3.2 and 3.3 present AI usage across different firm sizes and age groups.

Among sectors, and by size groups, service firms reported the highest average usage (not shown in figure) of this advanced digital technology, with 14 percent indicating AI adoption. In contrast, the average adoption rate among manufacturing and retail and wholesale firms was less than half that figure. Consistent with previous findings, larger firms were more likely to use AI than smaller firms. In some cases, the gap in adoption between large firms and micro, small, and medium-sized enterprises (MSMEs) was nearly three times as large.

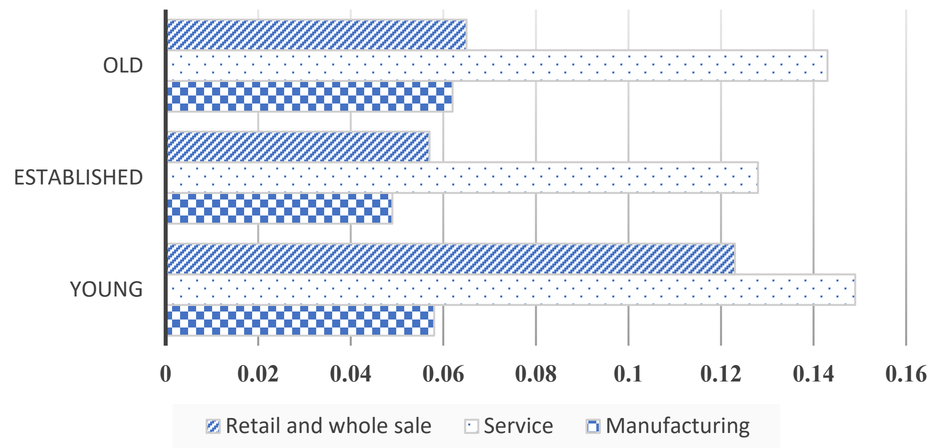
When examining AI use by firm age (Figure 3.3), younger firms in the services and retail and wholesale sectors were likelier to adopt AI than their older counterparts. In the manufacturing sector, however, the trend was reversed, with older firms showing higher rates of AI adoption.

Figure 3.2 Share of Colombian Firms Using AI across Size Groups



Source: Authors' calculations based on ENTIC-Dane.

Figure 3.3 Share of Colombian Firms Using AI across Age Groups



Source: Authors' calculations based on ENTIC-Dane.

As shown in the previous figures, the average adoption of AI among Colombian firms is not very low compared to data provided by recent research.

How does the use of AI by Colombian firms compare to other regions and countries? For context, Rammer, Fernández, and Czarnitzki (2022) reported that as early as 2017, 5.8 percent of German firms were actively using AI in their operations. However, the share of large German firms (more than 1,000 employees) using AI was 30.8 percent. Six years later, for German firms, Licht and Wohlrabe (2024), using a *different* survey, found that this share had increased to 13.3 percent in 2023 and rose further to 27 percent by 2024.

In the United States, reported adoption rates vary by study and survey year. Zolas et al. (2020) documented a mean AI adoption rate of 6.6 percent. McElheran et al. (2022), analyzing U.S. firms in 2017, reported a similar rate of 5.8 percent. Disaggregated by firm size, adoption rates were 2.7 percent for micro firms, 3.1 percent for small firms, 4 percent for medium firms, and over 10.5 percent for large firms. More recently, Bonney et al. (2024), using the Business Trends and Outlook Survey (BTOS), found that AI usage among firms was 3.7 percent in September 2023, increasing to 5.4 percent by February 2024. According to McElheran et al. (2025), AI adoption has grown significantly to 22.8 percent by 2021. Then, the high variation in the use of AI by firms in the USA responds to the different scope of surveys, samples of firms, and the like.

In the United Kingdom, Evans and Heimann (2022) reported that 15 percent of small firms had adopted at least one type of AI technology, compared to 34 percent of medium-sized firms and 68 percent of large firms.

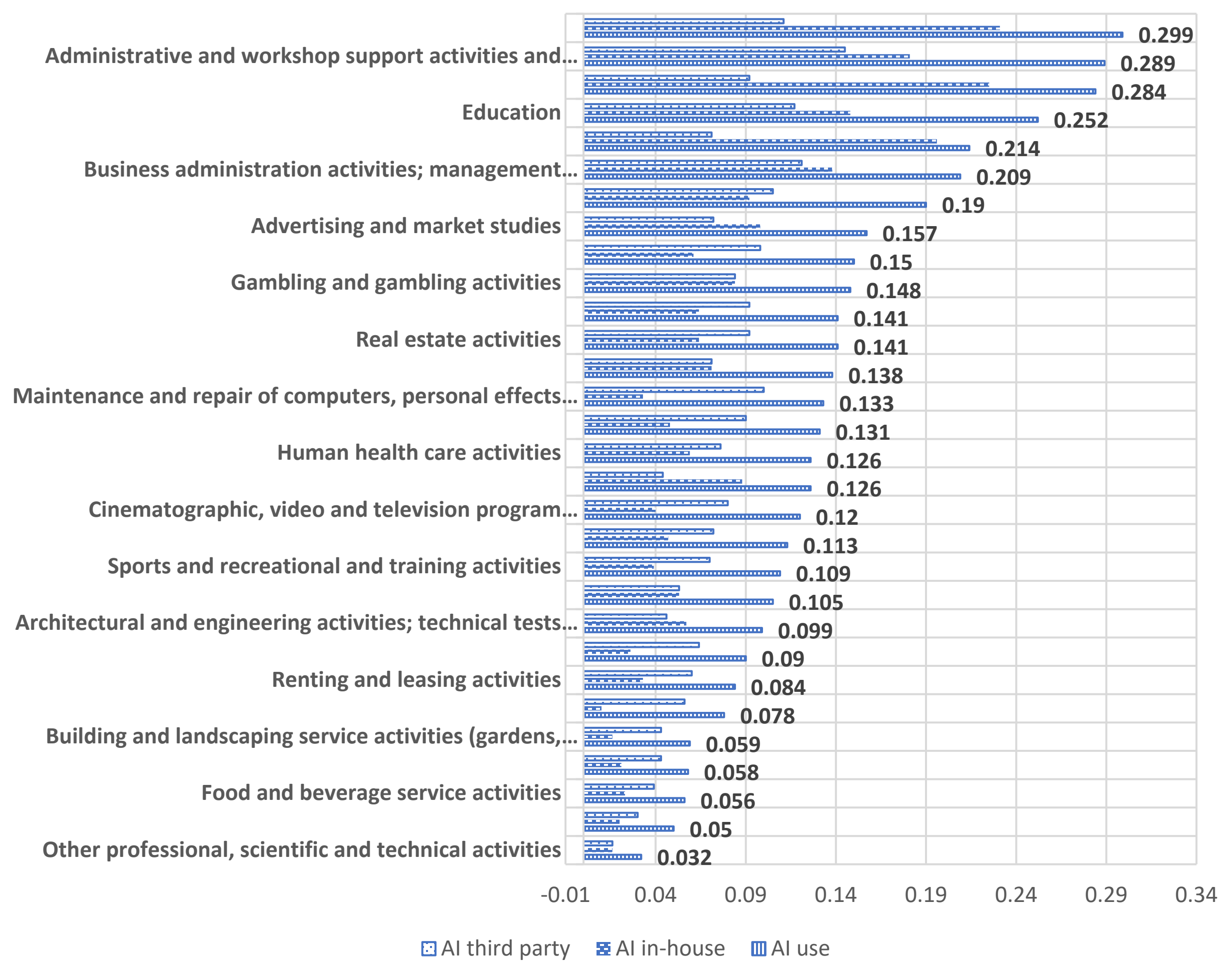
These figures highlight the rapid diffusion of artificial intelligence—a technology that some scholars categorize as a General-Purpose Technology (GPT) (Brynjolfsson and McAfee, 2017; McElheran et al., 2025). In general, the use of AI by firms in Colombia is relatively moderate.

3.2.3 AI Use at Granular Sector level

To provide a complementary view of firms' AI use by sector within services and manufacturing, specifically at the 2-digit ISIC level (Colombian CIIU Rev. 4), Figures 3.4 and 3.5 present the facts. This more granular analysis reveals significant variation. In Figure 3.4, six service sectors—including business administration, management consultancy, scientific research and development, education, computer systems development (planning, analysis, design, programming, testing), IT consultancy, administrative support, and information services—report AI adoption rates exceeding 20 percent, with one nearing 30 percent. Notably, in-house AI development exceeds 15 percent in five of these sectors. As expected, most firms rely on third-party providers as their primary source of AI solutions.

The service sectors using AI more intensively are to some extent like the service sectors using AI in European countries: Telecommunications, IT services, scientific R&D are among the seven heavy user of AI in Europe (Calvino et al., 2024). Interestingly, the share of firms using AI in those sectors are comparable to the one reported for the EU27+Norway and Turkiye.

Figure 3.4 Share of Colombian Firms Using AI in Service Sectors, ISIC- 2 digits

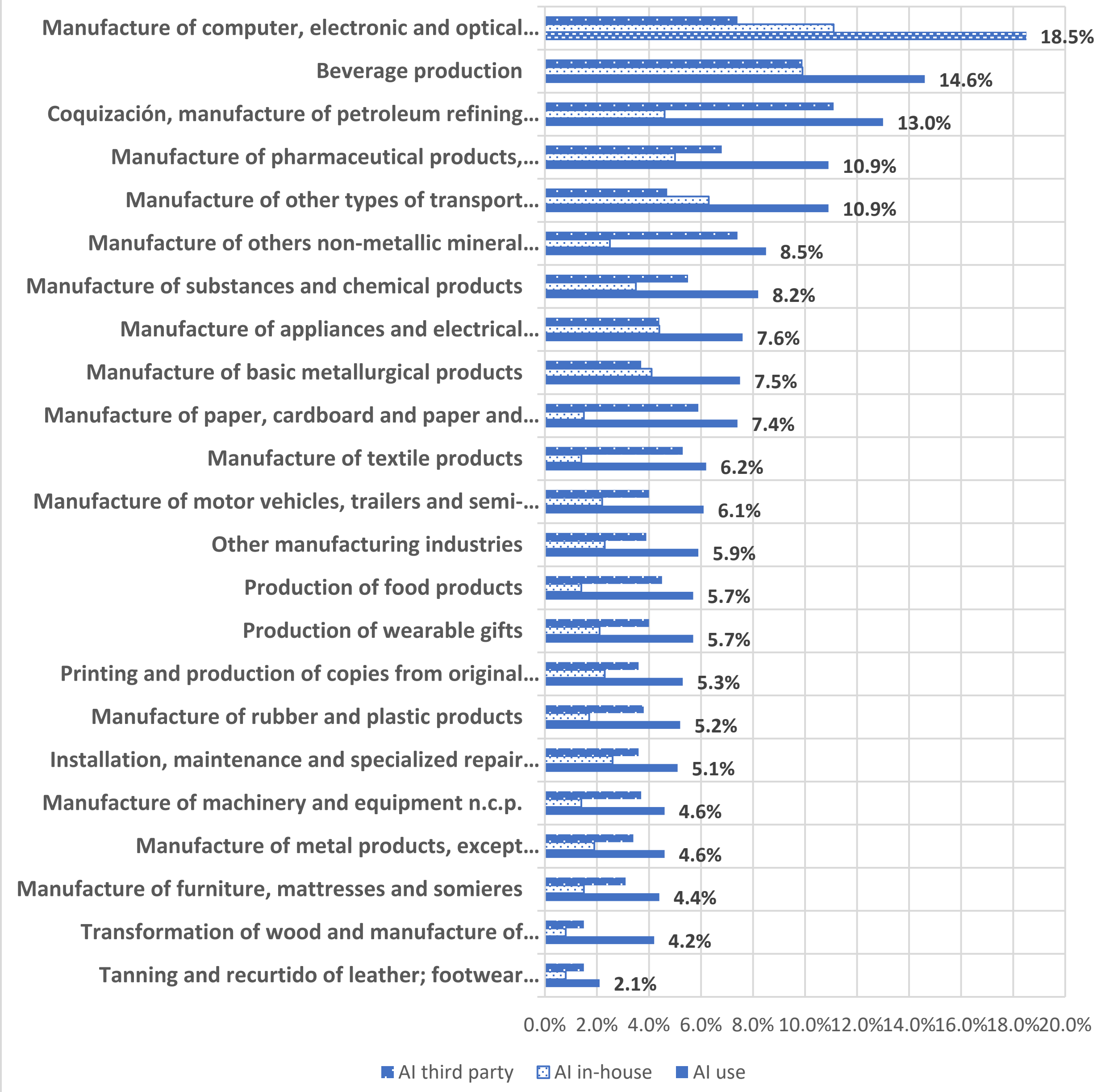


Source: Authors' calculations based on ENTIC-Dane.

Figure 3.5 illustrates the share of manufacturing firms utilizing AI, categorized by 2-digit ISIC industry. Compared to the service sector, the diffusion of AI in manufacturing has been significantly slower. In five sectors—namely the manufacture of other transport equipment, pharmaceutical products, petroleum and byproducts, beverages, and computer, electronic, and optical products—AI adoption rates ranged from just over 10 percent to under 19 percent. As in the service sector, third-party providers remain the primary source of AI solutions.

The manufacturing sectors using AI more intensively in Europe were in 2021 (2023) computer and electronics, transport and equipment, chemicals, machinery and equipment, and rubber, plastics and mineral (Calvino et al., 2024). To some extent these are the same sectors using intensively AI by Colombian manufacturing firms.

Figure 3.5 Share of Colombian Firms Using AI in Manufacturing Sectors



Source: Authors' calculations based on ENTIC-Dane.

3.2.4 Complementary Factors and Controls

Recent studies (Akerman, Gaarder, and Mogstad, 2015; Brynjolfsson, Rock, and Syverson, 2021; Calvino et al., 2022; Corò and Volpe, 2020; Crouzet et al., 2022; Ohlert, Giering, and Kirchner, 2022; Calvino and Fontanelli, 2023; Cho et al., 2023; Justy et al., 2023; Jung and Gómez-Bengoechea, 2025) have highlighted the role of complementary factors or technologies that facilitate the use or adoption of other medium or advanced digital technologies. At the firm level, the most analyzed factors include a) the presence of skilled workers, b) managerial capabilities, c) ICT training for employees, intangible capital, d) patents and blueprints, e) investment in databases and Software, including ICT-related investments, and f) organizational capital.

To proceed in a structured way—and considering that the three surveys used in this study contain different and limited sets of questions regarding these complementary factors—we present in Appendix Tables 2 to 4 for each country and the specific factors included in the empirical analysis of digital technology adoption, disaggregated by firm size and age groups, and economic sector. The definitions of all these variables by country are also presented in the tables in the Appendix. The surveys in Ecuador and Colombia ask about the use of digital networks, such as intranets, extranets, and LANs. To simplify the analysis, we calculated a network intensity index as the average of the firms' usage of networks.

Further, in Appendix Tables 11 to 16 report the correlation matrices for the main variables used in the empirical exercises, and for the three countries (for Colombian firms, discriminated across sectors). The correlation among variables is relatively low, except for those related to specialized management software, which reinforces the insight that firms may use them in a bundle.

3.2.5 Epidemic or Spillover Effects

The extensive literature on technology diffusion (Rogers, 1983; Karshenas and Stoneman, 1993; Dahlke et al., 2024) highlights several aspects of the diffusion process. Dahlke et al. (2024) synthesize the diffusion process as follows. First, the diffusion of knowledge and its transmission between firms play a crucial role in adopting new technologies. Knowledge dissemination is facilitated through broad-based (mass media) and localized (interpersonal) communication channels. Once a firm decides to adopt a technology, the process progresses through stages of integration into business operations. This process underscores the significance of inter-firm information flows, which can generate positive network externalities that influence adoption decisions regarding emerging technologies.

Knowledge spillovers across firms often underpin such dynamics. There enters the concept of “epidemic effects” that are particularly pertinent to the spread of digital technologies, which typically involve, in some cases, lower capital investment but carry significant uncertainty regarding short-term returns. Epidemic effects refer to endogenous learning processes whereby information about a new technology propagates and intensifies as more firms adopt it. As the technology spreads, early exposure to knowledge accelerates further diffusion, gradually reducing uncertainty and enhancing perceived benefits through established networks. Spillover or "epidemic effects" then encompass learning and non-market intermediated externalities. These effects may also arise from a firm's prior experience with similar technologies or observing other firms' adoption and use of new technologies.

To capture this epidemic or spillover effects, we include a variable we call "spillover." This variable is constructed following the approach of Gallego et al., (2015) and Cette, Nevoux, and Py (2022).

$$Spillover\_k_{it} = \frac{\sum_{i \neq j} \quad k_{it}}{N-1} \qquad (1)$$

where k_{it} denotes the digital technology variable of a firm belonging to the same sector as firm *j* in year *t*. This leave-one-out mean is computed on the other medium digital technologies in the four countries.

4. Empirical Framework and Main Results of Factors Associated with the Use of AI and Cloud Computing

This section presents the results of the factors associated with using some digital technologies available across the four countries.

4.1 Empirical Framework

The starting point of our econometric analysis is identifying the factors associated with adopting specific digital technologies. Two critical considerations guide this analysis. First, the digital technology indicators are binary (i.e., yes/no responses), which calls for appropriate econometric techniques. We employ linear probability models (LPM) since we are only interested in the linear association of the internal factors with the two digital technologies. Second, the set of complementary or enabling variables and control variables varies across the three countries, reflecting differences in survey design and institutional contexts.

The model specification for all the digital technologies is:

$$y_{ikt} = \beta_i + \beta_t + \beta_r + \beta_s + \beta_1 X_{i,t} + \beta_2 \Gamma_{i,t} + \varepsilon_{it} \qquad (2)$$

where y_{ikt} a binary variable represents the use of any of the digital technology (k) by a firm i in a country. If a firm (i) employs a technology (k), the variable is equal to 1; if not, it is zero. The vector X_{it} represents the complementary or enabling ICT factors of a firm's use of technology (k) (See Figure 3.1). Last, the vector Γ_i controls for other non-ICT variables, firm characteristics, like export, foreign capital, and the like presented above, as well as outside-firm factors. The reader should remember that these enabling ICT and non-ICT variables differ from country to country. The other terms are controls by time, region, and sector effects.

4.2 Empirical Results

We first present the results on the determinants of *cloud computing* use in Chile, Ecuador, and Colombia. Later, we analyze the factors associated to the use of AI for Colombian firms since questions on using artificial intelligence are available in the ENTIC survey for Colombia.

We constructed group categories for all countries to analyze the effects of size and firm age. The size group is composed of *micro* – the reference one- (≤ 9 employees), *small* (10 to 49 employees), *medium* (50 to 249 employees), and *large* firms (> 249 employees). The age group is composed of *young* firms – the reference one- (less than 6 years), *established* (6 to 10 years), and *old* firms (more than 10 years). In the case of Chile, the number of firms in the micro-size category was too small, so we consolidated the groups into only three size categories.

4.2.1 Factors Associated with the Use of Cloud Computing

Table 4.1 presents the results of the LPMs on the associations between some complementary factors, firm characteristics, and other variables, as outlined in equation (2) above on the use of cloud computing for firms in Chile, Ecuador, and Colombia. Given its essential role as enabling technology, we start the analysis with cloud computing. As mentioned above, cloud computing as Software as a service (SaaS) can "*deliver computing services—data storage, computation, and networking—to users at the time, to the location and in the quantity they wish to consume, with costs based only on the resources used. Users simply procure the "amount of computing" they want from providers without investing in computing infrastru*cture. (Kushida, Murray, Zysman 2011, p. 211)." This technology enhances firms' operations, reduces costs, enhances firm survival, and enables innovation and productivity (Jin and McElheran, 2018; DeStefano, Kneller, Timmis, 2023; Zhen et al., 2023).

Table 4.1 is organized into three panels, each offering key insights. First, firms with ICT-related enablers—such as access to fast broadband and employee training in ICT use (In Ecuador and Colombia)—are more likely to adopt cloud computing across all three countries. This supports the finding by DeStefano, Kneller, and Timmis (2022), who note that "the growth of cloud services has gone hand-in-hand with the diffusion of high-speed fiber broadband." Second, the evidence partially shows that spillover effects—referred to by Battisti, Canepa, and Stoneman (2009) as "epidemic effects"—are associated with increased cloud adoption in two Chilean and Ecuadorian sectors. These effects include both learning from others and non-market externalities, which can stem from a firm's own past experiences or from observing peer adoption. Among the factors analyzed, these spillover effects appear to be among the strongest drivers of cloud computing adoption—except in the case of Colombian firms.

Next, in the second panel, there are some other factors internal and external to the firms that have been found relevant in other contexts (Calvino et al., 2022). Clearly the most intense is the use of digital networks like intranet, extranet, Lan, and the greater use of specialized management software the higher is that firms adopt cloud computing. This result was expected since most of these specialized management applications serve as SaaS. Research on the adoption of digital technologies (Forman, 2005, Calvino et al., 2022; Calvino & Fontanelli, 2023; Cho et al., 2023) have emphasized the role of human capital as an enabler of the use of this type of technologies. We found that firms with high-skilled employees, measured as the share of employees with at least a bachelor's degree,e are more prone to use cloud computing.

Some scholars argue that firms that are more embedded in external relations, such as those that sell abroad or have foreign ownership, are also more likely to adopt modern digital technologies (Nachum and Zaheer 2005; Iammarino and McCann, 2013). Competition incentives lead firms to use them. We find positive association of these two factors, although in some cases they are not statistically significant. Lastly, more productive firms, which measure productivity using the ratio of sales to the number of employees, are in some sector-country more likely to utilize cloud computing. However, in some cases, there were not any statistical effects, or the effect was negative.

Finally, the bottom panel of the table presents results by firm size and age. No consistent pattern emerges regarding whether firm size or age drives the adoption of cloud computing. Large firms in the manufacturing and retail and wholesale sectors in Ecuador and retail and wholesale, and service sectors in Colombia appear more likely to adopt this technology.

Table 4.1 Determinants of the Use of Cloud Computing

Variables	Chile			Ecuador			Colombia		
	Manufacturing	Commerce	Services	Manufacturing	Commerce	Services	Manufacturing	Commerce	Services
ICT investment (D)	0.112	0.044	0.118	0.101	0.029	0.080	-0.028	n.a.	0.109***
	(0.128)	(0.166)	(0.102)	(0.071)	(0.044)	(0.058)	(0.041)		(0.039)
Training ICT employees (D)	0.268**	0.092	0.146	0.171**	0.147***	0.238***	0.757***	0.694***	0.848***
	(0.107)	(0.149)	(0.093)	(0.075)	(0.051)	(0.060)	(0.045)	(0.056)	(0.042)
Cloud spillovers	2.020**	2.214***	1.947***	1.807***	2.003***	1.964***	0.049	-0.005	0.375***
	(0.860)	(0.849)	(0.570)	(0.165)	(0.163)	(0.123)	(0.061)	(0.129)	(0.057)
Fast broadband > 100 Mbps (D)	0.196**	0.250*	0.137	0.225**	0.211***	0.430***	0.216***	0.147***	0.066*
	(0.097)	(0.137)	(0.086)	(0.105)	(0.062)	(0.075)	(0.048)	(0.057)	(0.039)
Social Network use	0.209**	0.343**	0.266***	0.285***	0.147***	0.428***	0.225***	0.060	0.202***
	(0.100)	(0.138)	(0.089)	(0.069)	(0.046)	(0.062)	(0.041)	(0.055)	(0.044)
Nets intensity use	n.a.	n.a.	n.a.	0.319**	0.405***	0.443***	0.498***	0.320***	0.361***
				(0.128)	(0.077)	(0.098)	(0.090)	(0.101)	(0.074)
Specialized management software intensity	2.443***	1.887***	2.412***	0.655***	0.710***	0.728***	2.182***	2.236***	1.780***
	(0.245)	(0.349)	(0.213)	(0.124)	(0.071)	(0.091)	(0.138)	(0.170)	(0.114)
% of employees with at least a college degree ++/	0.509**	0.425*	0.445***	1.289**	0.305	0.036	0.289**	1.100***	0.383**
	(0.208)	(0.224)	(0.128)	(0.516)	(0.193)	(0.137)	(0.142)	(0.253)	(0.160)
Labor productivity (log)	0.117***	0.105*	0.038	0.130**	0.063**	-0.021	0.035*	0.005	0.023
	(0.044)	(0.057)	(0.031)	(0.053)	(0.031)	(0.032)	(0.021)	(0.030)	(0.020)
Export (D)	0.152	0.071	-0.043	0.165**	0.250***	0.132	-0.014	n.a.	n.a.
	(0.110)	(0.175)	(0.144)	(0.078)	(0.066)	(0.086)	(0.046)		
Foreign capital (D)	0.011	-0.448**	0.020	0.096	0.169**	0.045	0.123	n.a.	n.a.
	(0.150)	(0.208)	(0.144)	(0.094)	(0.081)	(0.080)	(0.091)		
Small (10-49)	n.a.	n.a.	n.a.	0.172	0.097	-0.384***	0.107*	0.141	0.259*
				(0.312)	(0.076)	(0.131)	(0.063)	(0.120)	(0.1101)
Medium (50-249)	-0.626**	-0.259	0.016	0.202	0.237***	-0.276**	0.074	0.134	0.257**
	(0.283)	(0.281)	(0.176)	(0.312)	(0.089)	(0.135)	(0.075)	(0.128)	(0.106)
Large (> 249)	-0.400	0.193	0.196	0.504	0.394***	-0.247	0.084	0.407***	0.197*
	(0.245)	(0.273)	(0.172)	(0.324)	(0.128)	(0.153)	(0.104)	(0.153)	(0.114)
Established (6-10)	0.374	-0.038	-0.072	0.252	0.054	0.105	0.235	0.039	-0.022
	(0.304)	(0.302)	(0.181)	(0.166)	(0.078)	(0.112)	(0.177)	(0.169)	(0.087)
Old > 10	0.285	0.247	-0.274*	0.381**	-0.026	0.108	0.138	-0.034	-0.072
	(0.276)	(0.276)	(0.165)	(0.159)	(0.075)	(0.101)	(0.157)	(0.155)	(0.075)
# Radio bases (log)	0.294	-0.333	-0.613	-0.001	0.034	0.010	n.a.	n.a.	n.a.
	(0.431)	(0.407)	(0.423)	(0.047)	(0.027)	(0.034)			
# Internet business connections	-0.198	0.280	0.267	n.a.	n.a.	n.a.	0.116	n.a.	0.108
	(0.398)	(0.450)	(0.396)				(0.073)		(0.069)
# STEM Fields graduates	-0.003	0.034	0.373	n.a.	n.a.	n.a.	-0.075	n.a.	0.028
	(0.261)	(0.297)	(0.278)				(0.061)		(0.081)
Constant	-4.339***	-5.526***	-5.477***	-3.372***	-2.558***	-1.317***	-3.329***	-2.244***	-3.745***
	(1.549)	(1.961)	(1.584)	(0.693)	(0.364)	(0.443)	(0.497)	(0.444)	(0.525)
Observations	2281	1359	2473	4,686	10,049	6,812	11914	7305	9517
Number of id_firm	1627	1167	1890	975	2,254	1,986	6330	3899	5374

Source: Author calculations based on ELE-Chile, ENESEM-Ecuador, and ENTIC-Colombia. Notes: +/ In the case of Colombia, it refers to business connections. ++/ For Ecuador, the variable is the ratio of number of professionals over total employees. This table reports the results from a regression based on equation (1) of the determinants of the use of cloud computing. For firm size, the reference group is micro firms while for firm age, the reference group is "young" firms. Clustered standard errors at firm level in parentheses: * Coefficient is statistically significant at the 10 percent level; ** at the 5 percent level; *** at the 1 percent level; no asterisk means the coefficient is not different from zero with statistical significance. n.a. = not applicable.

4.3 Factors Associated with the Use of Artificial Intelligence

Research on the factors influencing the adoption of artificial intelligence (AI) is still emerging, with most existing studies focusing on European contexts. Notable contributions include Calvino and Fontanelli (2023, 2024), who analyze a sample of French firms; McElheran et al. (2023), who examine a large dataset of U.S. firms; and Brey and van der Marel (2024), who investigate AI adoption across various sectors in European countries. The most recent and comprehensive analysis is provided by McElheran et al. (2025), who use data from the 2021 Management and Organizational Practices Survey (MOPS)—a supplement to the 2021 Annual Survey of Manufactures (ASM)—to explore the determinants of AI adoption among U.S. manufacturing firms.

Recently, Herrera et al. investigated the determinants of AI adoption among Colombian manufacturing firms, distinguishing between in-house development and subcontracting. Their findings indicate that large firms are more likely to adopt AI technologies. Furthermore, complementary factors such as effective management, a higher share of employees with at least a college degree, and engagement in patenting activities were found to be positively associated with AI adoption.

In this study, we extend the analysis to include firms in the services and retail and wholesale sectors. Additionally, we incorporate a new set of explanatory variables, which contributes to the novelty and strength of this study.

Table 4.2 presents the results of an OLS model. A key finding is the positive impact of cloud computing adoption on the likelihood of firms using AI. This effect is consistent across all three sectors analyzed. This finding aligns with those of McElheran et al. (2025), who also report a positive correlation between cloud computing and AI adoption among U.S. manufacturing firms.

Additionally, firms with access to high-speed broadband connections (exceeding 100 Mbps) and those that provide ICT training to their employees are more likely to adopt AI. Given that AI is a relatively new technology and still in the early stages of diffusion, as illustrated in Figures 3.2 and 3.3, service firms are at the forefront of adoption, which may explain why spillover effects are only significant in this sector.

Furthermore, firms using more specialized management software are more likely to adopt AI, a relationship supported by Ångström et al. (2023), who emphasize the growing integration between such software and AI tools (Pournader et al., 2021; Basu et al., 2023; Chowdhury et al., 2023; Mikalef et al., 2023; Culot, Podrecca, and Nassimbeni, 2024). The findings in Table 4.2 confirm this association: Colombian firms with greater intensity in the use of these technologies across all three sectors show higher probabilities of adopting AI. A similar positive relationship is observed with the intensive use of specialized networks.

Interestingly, the regression results resemble the descriptive findings in Section 3.2.2 regarding firm size. When compared to microenterprises (the reference group), there seems to be a consistent pattern linking firm size to AI adoption, particularly for large firms in the manufacturing and service sectors. While those firms are more likely to adopt AI, especially service firms, this pattern does not hold either for small and medium-sized manufacturing firms or for any size group in the retail and wholesale sector.

Table 4.2 Factors Associated with the Use of Artificial Intelligence by Colombian Firms

Variables	Manufacturing	Retail and wholesale	Services
ICT investment (D)	0.001	n.a.	-0.004
	(0.005)		(0.006)
Training ICT employees (D)	0.033**	0.013	0.039**
	(0.008)	(0.008)	(0.008)
Cloud computing	0.052***	0.066***	0.073***
	(0.007)	(0.008)	(0.008)
Fast broadband > 100 Mbps (D)	0.018**	0.021**	0.015**
	(0.007)	(0.008)	(0.007)
AI spillovers	-0.046**	-0.011	0.030
	(0.019)	(0.037)	(0.024)
Network intensity	0.022*	0.019	0.037***
	(0.011)	(0.013)	(0.013)
Specialized management software intensity	0.299***	0.312***	0.347***
	(0.027)	(0.032)	(0.023)
% of employees with a college degree	0.018	0.056	-0.134**
	(0.019)	(0.038)	(0.023)
Labor productivity	0.002	0.001	0.002
	(0.002)	(0.004)	(0.004)
Export (D)	0.005	n.a.	n.a.

	(0.006)		
Foreign capital (D)	-0.014	n.a.	n.a.
	(0.017)		
Small (10-49)	-0.001	-0.015	0.017
	(0.005)	(0.010)	(0.012)
Medium (50-249)	-0.010	-0.029*	0.023*
	(0.08)	(0.011)	(0.014)
Large (+ 250)	0.038**	0.003	0.037**
	(0.017)	(0.019)	(0.016)
Established (6-10)	0.029	-0.028	0.001
	(0.020)	(0.023)	(0.014)
Old > 10	0.035*	-0.035	-0.015
	(0.019)	(0.021)	(0.013)
Constant	-0.029*	0.016	-0.098
	(0.029)	(0.053)	(0.065)
Observations	11911	7305	10957
Number of id-firm	0.131	0.117	0.158

Robust standard errors clustered at firm level in parentheses *** p<0.01, ** p<0.05, * p<0.1

5. The Association of the Use of Cloud Computing and AI with Firm Performance

To examine the relationship between the use of cloud computing and AI on firm performance, we employ the following specification:

$$lny_{it} = \lambda_i + \alpha_k lnk_{it} + \alpha_l lnl_{it} + \alpha_m lnm_{it} + \alpha_{ai} AI_{it} + X_{i,t}\beta + \alpha_t + \gamma_R + \eta_S + \varepsilon_{it} \quad (3)$$

where y_{it} is firm sales (Value added), k is capital, l is labor, and m is material for manufacturing firms, or service costs for service firms, and merchandise costs for retail and wholesale firms.[4] The coefficient of interest measures the impact of AI use or cloud computing use. It is a binary variable that measures the firms' use of AI: in-house or contracted. Furthermore, we control for year, α_t region γ_R, and sector η_S (4-digit ISIC) fixed effects. A complementary exercise for Ecuador (CC) and Colombia (CC and AI) utilizes a model that measures labor productivity as value added

[4] Data on sales, value added, materials, and service costs are in real terms and have been deflated at the 2-digit sector level for most countries. In case of not having a deflator from National Accounts, we use CPI.

per employee. Additionally, it incorporates ICT complementary variables and controls for region, sector, and year fixed effects.

The literature on production function estimation typically assumes that firm-specific productivity is known to the firm but unobservable to the researcher. Since firms optimize their input choices based on this private information, endogeneity becomes a significant concern in econometric estimation. The primary source of endogeneity in regressions such as equation (3) is selection bias (Hamilton and Nickerson, 2003). Specifically, firms with higher performance or superior managerial capabilities are more likely to adopt CC or AI technologies more intensively, potentially biasing the estimated effects of these technologies on productivity.

5.1 Identification Strategy

In research examining the impact of artificial intelligence (AI) or cloud computing on firm performance, addressing endogeneity is crucial to ensure accurate estimations. Endogeneity can arise from simultaneity, omitted variables, or measurement errors. For instance, firms might choose to adopt AI or cloud technologies because they already enjoy higher profits or possess more significant financial resources—implying that productivity could influence AI and cloud computing adoption rather than the other way around (Hamilton and Nickerson, 2003). Additionally, given the data limitations in some surveys, our model may overlook important variables correlated with AI and cloud use, as well as their influence on productivity, resulting in biased estimates. Such omitted factors could include broader digitalization strategies, better organizational and management structures, and dynamic investments in technological infrastructure.

As established in the literature, addressing endogeneity concerns requires using instruments that are correlated with the endogenous variable but uncorrelated with unobserved productivity shocks. Cette et al. (2022) adopt an instrumental variable approach that utilizes Bartik-style instruments. These instruments exploit exogenous variation arising from the differential exposure of specific manufacturing industries to standard shocks—in this case, the introduction of CC or AI digital technologies. Specifically, this primary instrument captures the epidemic or spillover effect, as described in equation (1), and is constructed as a leave-one-out sectoral average of technology adoption (AI and cloud computing).

The studies by Czarnitzki et al. (2023) and DeStefano et al. (2023) approach the endogeneity concern using two-step procedure. First, they apply an entropy balancing to the variables used in the regressions.[5] The objective of this step is to reweight the control group to ensure that the first three moments—mean, variance, and skewness—of each matching variable are identical between treated firms (i.e., CC or AI adopters) and the control group (i.e., non-adopters). The second step consists of using the reweighting and applying an IV 2SLS.

We follow the same approach. First, to strengthen the validity of our observational approach, we apply entropy balancing[6] as an additional strategy to mitigate potential bias arising from unobserved heterogeneity. Then, we employ an instrumental variable approach, using the average use of the technology at sector-region-year levels in year *t*-1 as the sole instrument (the Bartik-style instrument). The IV 2SLS is run using the weights generated from the entropy balancing. We follow this procedure for cloud computing and AI effects on firms' sales. This procedure, we argue, offers a better estimate of the relationship between cloud computing and AI with firms' sales and labor productivity without guaranteeing a causal effect.

5.2 Colombia AI Use and Firm Sales: Baseline Model

We now present the estimated impact of AI use on firm sales. Table 5.1 reports the results for Colombia, where the main variable of interest is the use of AI. The first three columns display estimates from the OLS model, while the last three columns present results from the IV-2SLS specification.

The main findings are as follows. The first three columns show that AI is positively and significantly associated with productivity when measured in sales. This result holds even after controlling for several factors deemed important in the review of studies above. These factors include firm age (in years, ln firm age), skilled labor, foreign ownership, and export status. Notably, the estimated coefficient for manufacturing firms in column (1) is remarkably close to the 5.5 percent productivity gain reported by Czarnitzki et al. (2023). The productivity gain for service firms is more than double that of manufacturing (13.4 percent), reflecting perhaps the broader adoption of this technology by firms in this sector, as presented in Section 3.2.2. Retail

[5] Conti et al. also employ a method like entropy balancing—coarsened exact matching—to address potential selection bias. However, the authors caution that these results should not be interpreted as causal.

[6] We use the Stata ebalance command created by Hainmueller and Xu (2013).

and wholesale firms adopted this technology less, and the gains in productivity are much lower (2 percent).

5.2.1 Colombia AI and Performance: Endogeneity of Advanced Digital Technologies

The previous results should be interpreted as purely descriptive, and it is important to emphasize that this approach does not necessarily identify the causal effect of technology adoption on firm performance. To have a better approximation to a (Likely) causal effect, we implement the two steps described above and presented in the three right columns of Table 5.1. The positive relationship between AI adoption and sales persists for firms in both the manufacturing and service sectors. However, the effect is not statistically significant in the manufacturing sector. For service firms, the estimated effect of AI use on sales is relatively substantial at 11.9 percent, though lower than the estimate obtained without controlling for endogeneity. In the retail and wholesale sector, the negative and statistically insignificant effect of AI adoption on sales may reflect the sector's relatively low adoption rate of these technologies.

Table 5.1 Regressions Explaining Firm Sales as a Function of AI Use

	Manufacturing	Retail and wholesale	Service	Manufacturing	Retail and wholesale	Service
Variables	OLS			2SLS-IV - Entropy balancing		
AI	0.061***	0.020**	0.134***	0.019	-0.014	0.119***
	(0.018)	(0.006)	(0.031)	(0.016)	(0.016)	(0.056)
Employment (log)	0.508***	0.147***	0.568***	0.350***	0.159***	0.658***
	(0.022)	(0.017)	(0.019)	(0.006)	(0.003)	(0.010)
Capital (log)	0.087***		0.000	0.105***		0.000
	(0.007)		(0.001)	(0.003)		(0.001)
Inputs (log)	0.453***	0.855***	0.353***	0.561***	0.838***	0.299***
	(0.022)	(0.019)	(0.015)	(0.004)	(0.002)	(0.007)
Human capital	0.676***	0.712***	1.193***	0.646***	0.762***	1.490***
	(0.067)	(0.122)	(0.171)	(0.029)	(0.019)	(0.108)
Age (log)	-0.058***	-0.012**	-0.010	-0.031***	-0.028***	0.008
	(0.015)	(0.004)	(0.016)	(0.007)	(0.003)	(0.013)
Foreign ownership	0.183***			0.122***		

	(0.029)			(0.012)		
Export	0.094***			0.092***		
	(0.013)			(0.009)		
Constant	6.042***	2.019***	7,694***	4.711***	2.263***	7.776***
	(0.203)	(0.239)	(0.197)	(0.052)	(0.034)	(0.283)
Observations	12413	7396	3593	12413	7396	3593
R-squared	0.933	0.984	0.862	0.966	0.989	0.891
Sector-year-region FE	yes	yes	yes	yes	yes	yes

Robust standard errors clustered at firm level in parentheses *** p<0.01, ** p<0.05, * p<0.1

5.2.2 Colombia Cloud Computing Use and Firm Sales: Baseline Model

Table 5.2 reports the results of the association of the use of cloud computing on Colombian firms' sales. Briefly, we observe that for all the specifications, OLS and IV-2SLS, cloud computing has positive and significant association with sales. The positive effect of this technology on sales for manufacturing firms is not significant after implementing the two-step procedure explained above. Importantly, the size of coefficients for retail and wholesale, and service firms more than double when using the instrumental variable.

Table 5.2 Regression Explaining Firm Sales as a Function of Cloud Computing Use in Colombia

Variables	Manufacturing	Retail and wholesale	Service	Manufacturing	Retail and wholesale	Service
		OLS		IV (2SLS) with entropy balancing		
Cloud computing	0.052***	0.016***	0.052***	0.003	0.070***	0.133***
	(0.012)	(0.005)	(0.012)	(0.023)	(0.026)	(0.068)
Employment (log)	0.506***	0.142***	0.506***	0.495***	0.158***	0.603***
	(0.022)	(0.007)	(0.022)	(0.007)	(0.003)	(0.010)
Capital (log)	0.087***		0.087***	0.121***		0.001
	(0.007)		(0.007)	(0.003)		(0.001)
Material (log)	0.453***	0.853***	0.453***	0.428***	0.842***	0.326***
	(0.022)	(0.007)	(0.022)	(0.004)	(0.002)	(0.007)
Human capital	0.670***	0.673***	0.670***	0.783***	0.810***	0.432***
	(0.067)	(0.039)	(0.067)	(0.035)	(0.020)	(0.062)
Ln Age	-0.058***	-0.011***	-0.058***	-0.077***	-0.015***	0.005
	(0.015)	(0.005)	(0.015)	(0.008)	(0.003)	(0.014)
Foreign Ownership	0.179***			0.180***		
	(0.029)			(0.016)		

Export	0.094***			0.078***		
	(0.013)			(0.011)		
Constant	6.048***	2.016***	7.643***	6.036***	2166	7.617***
	(0.203)	(0.107)	(0.403)	(0.062)	(0.038)	(0.213)
Observations	12413	7396	3593	12413	7396	3593
R-squared	0.930	0.984	0.858	0.947	0.985	0.878
Sector-year- region FE	yes	yes	yes	yes	yes	yes

Robust standard errors clustered at firm level in parentheses *** p<0.01, ** p<0.05, * p<0.1

5.3 Chile Cloud Computing Use and Firm Sales: Baseline Model

Table 5.3 presents Ordinary Least Squares (OLS) and IV-2SLS regression results examining the relationship between cloud computing adoption and firm sales in Chile. The coefficients on the variable of interest are generally positive and statistically significant in the OLS specifications. However, statistical significance is lost for firms in the manufacturing and retail and wholesale sectors. When comparing sectoral effects, the OLS results suggest that retail and wholesale firms experience a broader association of performance with the use of cloud adoption. In contrast, the two-step procedure (IV-2SLS) estimates show a larger effect of cloud computing on sales only for service firms, although the magnitude appears unusually high.

Table 5.3 Regression Explaining Firm Sales as a Function of Cloud Computing Use in Chile

VARIABLES	**Manufacturing**	**Retail and wholesale**	**Service**	**Manufacturing**	**Retail and wholesale**	**Service**
	OLS			IV (2SLS) with entropy balancing		
CC	0.174***	0.304***	0.249***	-0.543*	0.225	1.003***
	(0.0406)	(0.0859)	(0.0558)	(0.302)	(0.261)	(0.322)
ln employees	0.389***	0.688***	0.532***	0.352***	0.690***	0.475***
	(0.0418)	(0.0245)	(0.0152)	(0.016)	(0.020)	(0.014)
ln capital	0.124***	0.117***	0.232***	0.139***	0.153***	0.239***
	(0.0151)	(0.0156)	(0.0112)	(0.010)	(0.015)	(0.010)
ln inputs	0.450***	0.0977***	0.0892***	0.493***	0.097***	0.093***
	(0.0438)	(0.00961)	(0.00517)	(0.010)	(0.007)	(0.005)
ln age	-0.00769	-0.0413	-0.111***	-0.027	-0.084*	-0.114***
	(0.0225)	(0.0414)	(0.0406)	(0.025)	(0.047)	(0.038)

Human capital	0.492***	1.079***	0.659***	0.558***	1.569***	0.661***
	(0.0726)	(0.117)	(0.0700)	(0.069)	(0.097)	(0.072)
Export (d)	0.115***	0.347***	0.109	0.086**	0.155**	0.070
	(0.0401)	(0.112)	(0.0693)	(0.036)	(0.077)	(0.070)
Foreign ownership	0.168***	0.437***	0.0633	0.096**	0.207**	0.038
	(0.0459)	(0.110)	(0.0815)	(0.042)	(0.081)	(0.067)
Constant	3.942***	7.183***	10.49***	3.818***	6.803***	10.830***
	(0.246)	(0.242)	(0.254)	(0.297)	(0.295)	(0.339)
Observations	2223	1265	2262	2223	1265	2262
R-squared	0.918	0.837	0.726	0.882	0.789	0.615
Sector year and region	FE	FE	FE	FE	FE	FE

*Robust standard errors clustered at firm level in parentheses *** p<0.01, ** p<0.05, * p<0.1*

5.4 Ecuador Cloud Computing Use and Firm Sales: Baseline Model

The results for Ecuadorian firms, shown in Table 5.4, indicate that the association between cloud computing adoption and sales is positive across almost all specifications. For the three sectors, the adoption of cloud computing is positively and significantly associated with firm sales in the specification that implements the two-step approach. The estimated impact is consistently larger for the service firms, followed by the retail and wholesale sector.

Table 5.4 Regression Explaining Firm Sales as a Function of Cloud Computing Use in Ecuador

VARIABLES	Manufacturing	Retail and wholesale	Service	Manufacturing	Retail and wholesale	Service
	OLS			IV (2SLS) with entropy balancing		
CC	0.073***	0.051**	0.023	0.142***	0.094	0.120***
	(0.022)	(0.025)	(0.036)	(0.032)	(0.088)	(0.045)
ln employees	0.378***	0.454***	0.485***	0.391***	0.482***	0.496***
	(0.020)	(0.020)	(0.026)	(0.008)	(0.008)	(0.009)
ln capital	0.003**	0.014***	0.013***	0.003**	0.015***	0.017***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)
ln inputs	0.472***	0.047***	0.082***	0.464***	0.035***	0.077***
	(0.028)	(0.009)	(0.010)	(0.006)	(0.005)	(0.005)
ln age	-0.008	0.027	0.043	-0.003	0.036***	0.048***
	(0.017)	(0.020)	(0.033)	(0.009)	(0.011)	(0.014)
Human capital	0.619***	0.263*	0.181*	0.507***	0.151**	0.388***

	(0.163)	(0.140)	(0.093)	(0.104)	(0.073)	(0.063)
Export (d)	0.087***	0.274***	0.221***	0.081***	0.199***	0.210***
	(0.024)	(0.043)	(0.059)	(0.014)	(0.020)	(0.029)
Foreign ownership	0.259***	0.342***	0.237***	0.227***	0.351***	0.238***
	(0.039)	(0.049)	(0.052)	(0.015)	(0.020)	(0.025)
Constant	6.960***	13.779***	12.851***	7.013***	13.807***	12.790***
	(0.402)	(0.128)	(0.256)	(0.091)	(0.081)	(0.113)
Observations	4590	9384	6451	4590	9384	6451
R-squared	0.867	0.508	0.581	0.879	0.524	0.589
Sector year & region	FE	FE	FE	FE	FE	FE

Robust standard errors clustered at firm level in parentheses *** p<0.01, ** p<0.05, * p<0.1

In summary, the results presented in Tables 5.1 to 5.4 are mostly aligned with the findings of Czarnitzki et al. (2023) and DeStefano et al. (2022), indicating that firms adopting artificial intelligence or cloud computing tend to exhibit improved performance. The productivity premiums obtained by firms associated with AI adoption (In the simple OLS model) across the three Colombian sectors are comparable to those reported in studies of the effects of adopting AI on performance. Filippucci et al. (2024) present the effects found in four studies. These effects range from (an average for some OECD countries) a low of 2.1 percent to a high of 4.4 percent in Czarnitzki et al. (2023) for German firms. The effect (statistically significant) for service firms was 11.9 percent, and for manufacturing firms, it was low (1.9 percent) and not significant.

As argued by Fountaine et al. (2019), only a few firms strongly engage in core practices that support AI adoption within their organizations. This insight can be complemented by the findings of McElheran et al. (2025, p. 33), who assert that old establishments experience productivity losses and that industrial AI adoption does not necessarily favor incumbents over entrants. This is particularly relevant for Colombian manufacturing firms. As shown in Table 3.1, about 94 percent of firms are ten years or older, and they can face some (of) "*the displacement of structured management practices and obliteration of knowledge management systems combining worker feedback and structured practices*." More research is warranted to discern whether Colombian manufacturing firms are facing the productivity J-curve, where short-term performance is weak but long-term performance can be strong.

Similarly, the positive association of cloud computing on sales observed in firms from Colombia, Chile, and Ecuador is substantial. When comparing results across these three countries, Chilean firms—on average larger than their Colombian and Ecuadorian counterparts—appear to benefit more from the adoption of cloud computing. In contrast, the effects on sales are relatively similar between Colombian and Ecuadorian firms.

5.5 Additional Results: Value-added as an Output Measure, Colombia and Ecuador

We assess the impact of cloud computing adoption on firms' labor productivity, measured as the ratio of value added to total employees (Calvino and Fontanelli, 2024). Table 5.4 presents the regression results for Ecuadorian firms using equation (3), applying the same approach to address potential endogeneity. The results from both the OLS and IV-2SLS specifications closely resemble those in Table 5.3, where firm sales were used as the performance variable. Firms in the service sector exhibit a greater productivity premium from cloud computing adoption compared to those in manufacturing and retail and wholesale sectors. The consistency of results across both performance measures and econometric specifications lends support to the positive—and possibly potentially causal—impact of cloud computing on firm performance. One plausible explanation for these favorable effects is the relatively very high adoption rate of cloud computing among firms, as well as its sustained use over time.

Tables 5.5 and 5.6 present the results of the productivity regressions for cloud computing and AI, respectively for Colombian firms. For cloud computing, although all coefficients are positive—indicating a productivity premium for adopting firms—only the estimate for the retail and wholesale sector remains weakly statistically significant after implementing the two-step procedure. The magnitude of the effect is comparable to that observed when using sales as the performance metric.

Table 5.5 Regression Explaining Firm Labor Productivity as a Function of Cloud Computing Use in Ecuador

	Manufacturing	Retail and wholesale	Service	Manufacturing	Retail and wholesale	Service
Variables		OLS		IV (2SLS) with entropy balancing		
CC	0.092***	0.072***	-0.015	0.123***	0.209***	0.232***
	(0.028)	(0.022)	(0.035)	(0.045)	(0.080)	(0.045)
ICT Training	0.147***	0.157***	0.114***	0.107***	0.102***	0.134***
	(0.027)	(0.023)	(0.026)	(0.020)	(0.017)	(0.022)
Fast Broadband	0.052	0.063**	0.184***	0.055**	0.053***	0.163***
	(0.034)	(0.028)	(0.034)	(0.026)	(0.020)	(0.025)
Specialized management software	0.142***	0.210***	0.020	0.114***	0.229***	-0.017
	(0.044)	(0.033)	(0.050)	(0.036)	(0.026)	(0.038)
log of # employees	-0.169***	-0.279***	-0.258***	-0.162***	-0.262***	-0.239***
	(0.021)	(0.016)	(0.024)	(0.009)	(0.006)	(0.009)
log of firm age	0.084***	0.169***	0.034	0.068***	0.172***	0.011
	(0.027)	(0.019)	(0.029)	(0.013)	(0.010)	(0.015)
Human capital	1.019***	0.689***	0.245***	0.936***	0.683***	0.458***
	(0.232)	(0.122)	(0.084)	(0.147)	(0.069)	(0.063)
Export	0.098***	0.166***	0.235***	0.097***	0.167***	0.121***
	(0.035)	(0.034)	(0.051)	(0.020)	(0.018)	(0.030)
Foreign ownership	0.319***	0.449***	0.269***	0.272***	0.479***	0.218***
	(0.045)	(0.043)	(0.053)	(0.022)	(0.020)	(0.028)
Constant	10.354***	10.495***	12.304***	10.414***	10.291***	12.259***
	(0.136)	(0.112)	(0.247)	(0.078)	(0.071)	(0.101)
Observations	4680	9739	6788	4680	9739	6788
R-squared	0.226	0.314	0.413	0.270	0.317	0.395
Sector year and region	FE	FE	FE	FE	FE	FE

Robust standard errors clustered at firm level in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Regarding the association of AI with firm labor productivity, the OLS models suggest a positive association; however, none of the coefficients are statistically significant. In the IV-2SLS specification, the effect remains positive but still non-significant for service firms. For manufacturing and retail and wholesale firms, the estimated effects turn negative, with the result being statistically significant for the latter.

Table 5.6 Regression Explaining Firm Labor Productivity as a Function of AI Use in Colombia

	Manufacturing	Retail and wholesale	Service	Manufacturing	Retail and wholesale	Service
Variables	OLS			IV (2SLS) with entropy balancing		
CC	0.010	0.026	0.056	-0.033	-0.209***	0.013
	(0.044)	(0.041)	(0.042)	(0.037)	(0.075)	(0.078)
ICT Training	0.043*	0.059**	0.069**	0.086***	0.082***	0.072**
	(0.019)	(0.024)	(0.031)	(0.020)	(0.023)	(0.034)
Fast broadband	0.102***	0.095***	0.168***	0.135***	0.138***	0.189***
	(0.027)	(0.026)	(0.032)	(0.019)	(0.021)	(0.028)
Specialized management software	0.712***	0.378***	0.688***	0.614***	0.355***	0.582***
	(0.078)	(0.078)	(0.089)	(0.036)	(0.040)	(0.058)
log of # employees	0.124***	-0.080***	-0.176***	0.047***	-0.080***	-0.134***
	(0.015)	(0.016)	(0.019)	(0.008)	(0.009)	(0.011)
log of firm age	-0.015	0.019	-0.028	0.038*	-0.093***	-0.011
	(0.024)	(0.022)	(0.019)	(0.015)	(0.015)	(0.018)
Human capital	1.146***	3.099***	1,985***	1.308***	3.670***	2.277***
	(0.122)	(0.143)	(0.206)	(0.063)	(0.084)	(0.140)
Export	0.305***			0.356***		
	(0.027)			(0.021)		
Foreign ownership	0.420***			0.518***		
	(0.067)			(0.031)		
Constant	10.059***	10.836***	10.595***	10.213***	11.151***	10.379***
	(0.122)	(0.114)	(0.278)	(0.079)	(0.079)	(0.240)
Observations	13028	7396	4274	13028	7396	4274
R-squared	0.286	0.284	0.332	0.433	0.372	0.341
Sector year & region	FE	FE	FE	FE	FE	FE

Robust standard errors clustered at firm level in parentheses *** p<0.01, ** p<0.05, * p<0.1

6. Conclusions

This study provides novel evidence on the adoption, association with, and impact of medium and advanced digital technologies on firm performance in three Latin American countries. The analysis is structured into four main sections. The third section presents descriptive evidence on the adoption patterns of various digital technologies across different firm ages, firm sizes, and broad economic sectors. The fourth section investigates the relationship between medium-level digital technologies and several internal and external complementary factors, employing panel data with random effects models. This section also focuses on the factors associated with the use of artificial intelligence (AI) among Colombian firms across the manufacturing, retail and wholesale, and service sectors. The final section examines whether the adoption of AI and cloud computing leads to or is associated with better firm performance, providing a first glimpse into these dynamics in a developing country context.

Recent empirical research based on firm-level data from Europe and the United States has focused on advanced digital technologies such as AI, big data, the Internet of Things (IoT), and cloud computing (Calvino et al., 2018, 2022, 2023; Zolas et al., 2021; McElheran, 2024; McElheran, 2025). These studies consistently find that larger and, in most cases, older firms are the primary adopters of these technologies. The information and communication technology (ICT) and professional services sectors, particularly, are identified as intensive users of AI and cloud computing. The concentration of digital technology adoption among large and mature firms has prompted scholars to question whether this pattern is driven by selection effects or by the causal impacts of technology adoption (Acemoglu et al., 2023).

The patterns of the digital technology adoption—specifically cloud computing and AI—in Chile, Colombia, and Ecuador largely mirror those observed in Europe and the United States. Larger firms are more likely to adopt these technologies than medium-sized, small, or micro firms. However, no consistent pattern emerges concerning firm age, which may reflect the higher proportion of old firms in the country samples. Moreover, the adoption rates of these technologies do not appear to differ substantially across the manufacturing, retail and wholesale, and service sectors across the countries studied. The service (sub)sectors with a high share of firms using AI in Colombia largely mirror those identified in studies conducted in the United States and Europe.

Importantly, our analysis reveals that the use of AI and cloud computing is positively associated with higher firm sales and, in some cases, with labor productivity. These findings underscore a potential role for public policy in facilitating digital transformation. One area for government intervention is to support firms in providing specialized training to employees using advanced technologies. This is particularly relevant considering concerns that technologies such as AI may displace workers—especially those in routine or low-skilled occupations (Acemoglu and Restrepo, 2018; Lei and Kim, 2024; Zhang et al., 2024). Calvino et al. (2022), in their study on the AI adoption gap in Italy, advocate for policies that enhance managerial capabilities, increase R&D investment, and improve firms' access to high-speed broadband infrastructure. In this regard, public support to the use of cloud computing as a SaaS should be placed at the top of the ICT agenda.

Micro, small, and medium-sized enterprises (MSMEs) constitute most of the business landscape across Latin American countries, and as such, they should be the primary focus of digitalization policies. Governments in the region should implement specific policies. The first step should be to raise awareness among these firms about the tangible benefits associated with adopting digital technologies. In this context, the Inter-American Development Bank (IDB), in collaboration with various public institutions (e.g., Ministries) and private sector actors across the region, has introduced a tool titled *Digital Checkup: How to Accelerate the Digital Transformation of MSMEs in Latin America and the Caribbean (LAC) (2021)*. This initiative provides firms with a framework to assess their current position on the digitalization ladder and identify the next steps for advancement. Eighteen LA countries are part of this initiative launched in 2021-2022. However, there has not been a repository of data or studies of progress that allow people and researchers to know the state of digital maturity of MSMEs across countries and whether the initiative has been successful, and what factors could have inhibited or fostered MSMEs from entering the platform, and the like. Furthermore, are there any plans to follow up on this important and relevant initiative?

Second, and perhaps more importantly, effective policymaking to foster the adoption of advanced digital technologies and reduce the growing digital divide among firms of different sizes depends on stronger and more comprehensive data on the adoption of digital technologies. ICT ministries, working alongside national statistical offices, should allocate more resources to regularly surveying firms about their use of digital technologies. At present, surveys such as Chile's ELE and Ecuador's ENESEM include only limited modules on basic and medium-level digital technologies. These should be updated to include questions on the adoption of advanced digital tools. Additionally, surveys should collect more detailed information on complementary factors—such as whether technologies are adopted in bundles (Cho et al., 2023), in sequence, or with synergies. They should also explore the purposes for which these technologies are used within firms' functional areas and the impact they have had. Finally, one key question in the surveys is to what extent cloud computing and AI are engaged in core practices across the organization (Fountaine et al., 2019). Given the growing focus on AI in recent research, such updates would also allow a more apparent distinction between AI adopters and users of other advanced technologies.

This study is based on three different surveys, each with its scope and objectives. A key limitation has been the challenge of constructing standardized metrics for digital technology use and for internal and external factors, which would enable pooling data across countries. This standardization is essential for assessing whether broader macro-level policies—such as regulations, the rollout of advanced infrastructure (e.g., fiber-optic networks), and national initiatives providing financial support (e.g., subsidies, tax credits, support for AI startups, and incentives for collaboration between firms, research centers, universities, and governments)—have been effective in promoting the adoption of advanced digital technologies. These external factors likely play a significant role in explaining the variation in the adoption rates of these advanced-digital tools. Having harmonized data on technology use across countries would significantly enhance our ability to evaluate these influences.

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Appendix

Appendix Table 1. Definition of Digital Technologies: Chile

Technology	**Definitions**
Cloud Computing (D)	Cloud computing software (computer services via the Internet; computing power, storage capacity, among others)
Social Network (D)	Does your company use social media?
e-commerce (D)	During year t, did you engage in e-commerce?
ICT expenditure (D)	Expenses on communication services and ICTs (telephone, internet, mail, computer support, etc.)
Management applications	
ERP (D)	ERP (Enterprise Resource Planning) software to manage the processes and information of different business areas of the company in an integrated manner
SMC (D)	Sales, marketing, and customer management software (control of cash registers, points of sale, and similar
CSS (D)	Computer security software (antivirus, firewall, encryption systems, among others)
MES (D)	Software specific to the business (reservation system, process control, traceability, among others)
Management software intensity	Mean over the sum of ERP, CRM, MES, CSS

Source: Chile ELE, INE.

Appendix Table 2. Definition of Digital Technologies: Ecuador

Technology	Definitions
ICT investment (D)	did the company use IT, communication equipment, and services?
Intranet (D)	did the company use IT, communication equipment, and services? Intranet
Extranet (D)	did the company use IT, communication equipment, and services? Extranet
Lan (D)	did the company use IT, communication equipment, and services? Lan
Network intensity	Mean over the sum over intranet, extranet, and Lan
Social networks (D)	In year t, which Social Network did your company use?
Own software (D)	In year t, did your company develop its software?
Training ICT employees (D)	In year *t,* did your company train its employees on using ICT?
Management applications	
CRM	Which of the following business activities are supported by the use of ICT? Management of customer relationships

OCM	Which of the following business activities are supported by the use of ICT? Order control and tracking management
FBM	Which of the following business activities are supported by the use of ICT? Financial business management
HRM	Which of the following business activities are supported by the use of ICT? Human resources management
SCM	Which of the following business activities are supported by the use of ICT? Supply chain management, logistics, inventory control
SSS	Which of the following business activities are supported by the use of ICT? Sales service and support
SPM	Which of the following business activities are supported by the use of ICT? Support for production development
KM	Which of the following business activities are supported by the use of ICT? Knowledge management
Management software intensity	Mean over the sum of the eight above applications

Source: Ecuador ENESEM, INEC.

Appendix Table 3. Definition of Digital Technologies: Colombia

Technology	Definitions
Intranet (D)	did the company use IT, communication equipment, and services? Intranet
Extranet (D)	did the company use IT, communication equipment, and services? Extranet
Wan (D)	did the company use IT, communication equipment, and services? Wan
Lan (D)	did the company use IT, communication equipment, and services? Lan
Network intensity	Mean over the sum over intranet, extranet, and Lan, Wan
Fast broadband	Tell the maximum speed of downloading your company has: > 100 Mbps
Web (own)	Does your company have its own page?
e-commerce (D)	During year *t*, did you engage in e-commerce?
Social networks (D)	Does your company have a formal policy for using social media by customers, suppliers, partners, or employees in year t?
Cloud Computing (D)	From the following list of methodologies or certifications, which ones did the company adopt for the development of its activities as of December 31, year t: cloud computing
Training ICT employees (D)	In year *t*, did your company train its employees on using ICT?
Management applications	
CRM	Which of the following business activities are supported by the use of ICT? Management of customer relationships

ERP	Which of the following business activities are supported by the use of ICT? Enterprise resource planning
PKI	Which of the following business activities are supported by the use of ICT? Public Key Infrastructure (PKI)
BPMN	Which of the following business activities are supported by the use of ICT? Business Process Model and Notation
SGDEA	Which of the following business activities are supported by the use of ICT? Electronic Archive Document Management Systems
RFID	Which of the following business activities are supported by the use of ICT? Radio Frequency Identification Devices
MDM	Which of the following business activities are supported by the use of ICT? Support for production development
GIS	Which of the following business activities are supported by the use of ICT? Geographic Information Systems
Management software intensity	Mean over the sum of the eight above applications

Source: Colombia ENTIC, Dane.

Appendix Table 4. Complementary and Control Variables: Chilean Firms

	Employees	Firm age	ICT training	Foreign ownership	Export	Proportion of employees with a college degree	Social Network	ICT expenditure (D)
Total	2530	18.80	0.327	0.0951	0.169	0.246	0.445	0.779
				Size				
Small	27.49	14.9	0.193	0.015	0.022	0.201	0.308	0.664
Medium	128.5	16.0	0.249	0.038	0.050	0.232	0.408	0.715
Large	4187	21.0	0.397	0.140	0.258	0.264	0.499	0.838
				Age				
Young	1365	3.6	0.234	0.0700	0.0586	0.235	0.484	0.750
Established	1968	8.1	0.284	0.0878	0.114	0.261	0.472	0.759
Old	2826	23.5	0.351	0.100	0.198	0.244	0.433	0.788
				Economic sectors				
Manufacturing	2356	22.2	0.376	0.114	0.331	0.181	0.387	0.829
Retail and wholesale	2348	17.2	0.257	0.082	0.072	0.186	0.430	0.729
Services	2783	16.6	0.322	0.086	0.078	0.336	0.505	0.762

Source: Author calculations based on ELE 3-4-5, INE.

Appendix Table 5. Complementary and Control Variables: Ecuadorian Firms

	Employees	Firm age	ICT training	Foreign ownership	Export	% employees who are professionals	Net intensity
	195	22	0.274	0.351	0.250	0.0796	0.496
Size							
Micro	5,4	13,8	0.0691	0.320	0.191	0.0673	0.317
Small	28	17	0.161	0.323	0.181	0.0726	0.408
Medium	114	23,4	0.313	0.355	0.260	0.0886	0.534
Large	803	30	0.490	0.408	0.387	0.0768	0.651
Age							
Young	99	3,7	0.330	0.209	0.0675	0.0750	0.694
Established	126	8,1	0.338	0.217	0.0679	0.0903	0.708
Old	226	27	0.355	0.266	0.0822	0.0733	0.731
Economic sectors							
Manufacturing	294	27,8	0.333	0.382	0.501	0.0451	0.533
Retail and wholesale	121	19,6	0.213	0.331	0.196	0.0581	0.452
Services	235	21,9	0.323	0.358	0.161	0.133	0.534

Source: Author calculations based on ENESEM 2015-2022, INEC.

Appendix Table 6. Complementary and Control Variables: Colombian Manufacturing Firms

	ICT investment (D)	Fast broadband > 100 Mbps	ICT training	Proportion of employees with a college degree	Foreign ownership	Management practice index	Investment in STI (D)	Export	Net intensity
	0.422	0.151	0.280	0.159	0.037	0.363	0.200	0.272	0.445
Size									
Micro	0.147	0.079	0.099	0.204	0.008	0.251	0.052	0.087	0.326
Small	0.308	0.109	0.170	0.146	0.008	0.313	0.129	0.170	0.391
Medium	0.649	0.203	0.447	0.153	0.064	0.449	0.304	0.435	0.527
Large	0.830	0.370	0.721	0.184	0.181	0.587	0.565	0.685	0.728
Age									
Young	0.424	0.122	0.281	0.164	0.007	0.401	0.401	0.165	0.475
Established	0.392	0.100	0.254	0.141	0.011	0.356	0.356	0.265	0.423
Old	0.355	0.154	0.282	0.160	0.039	0.363	0.363	0.275	0.447

Source: Author calculations based on ENTIC 2019-2020, Dane.

Appendix Table 7. Complementary and Control Variables: Colombian Retail and Wholesale Firms

	ICT investment (D)	Fast broadband > 100 Mbps	ICT training	Proportion of employees with a college degree	Management practice index	Investment in STI (D)	Net intensity
	0.886	0.192	0.377	0.105	0.378	0.143	0.503
Size							
Micro	0.776	0.118	0.130	0.117	0.336	0.123	0.322
Small	0.856	0.146	0.257	0.096	0.326	0.091	0.419
Medium	0.949	0.221	0.498	0.114	0.439	0.191	0.580
Large	0.988	0.386	0.703	0.112	0.541	0.340	0.767
Age							
Young	0.773	0.136	0.370	0.117	0.374	0.141	0.506
Established	0.841	0.161	0.283	0.094	0.368	0.119	0.472
Old	0.894	0.196	0.388	0.105	0.378	0.146	0.506

Source: Author calculations based on ENTIC 2019-2020, Dane.

Appendix Table 8. Complementary and Control Variables: Colombian Service Firms

	ICT investment (D)	Fast broadband > 100 Mbps	ICT training	Proportion of employees with a college degree	Management practice index	Investment in STI (D)	Net intensity
	0.554	0.307	0.456	0.092	0.283	0.120	0.557
Size							
Micro	0.218	0.238	0.251	0.063	0.078	0.181	0.405
Small	0.415	0.237	0.366	0.065	0.146	0.282	0.486
Medium	0.582	0.300	0.464	0.074	0.194	0.208	0.560
Large	0.733	0.402	0.576	0.105	0.347	0.340	0.656
Age							
Young	0.474	0.283	0.454	0.057	0.173	0.202	0.541
Established	0.472	0.287	0.422	0.056	0.165	0.217	0.515
Old	0.578	0.312	0.463	0.075	0.174	0.302	0.568

Source: Author calculations based on ENTIC 2019-2020, Dane.

Appendix Table 9. Pairwise Correlations: Chilean Firms

Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1. CRM	1								
2. ERP	0.247*	1							
3.MES	0.298*	0.309*	1						
4.CSS	0.299*	0.495*	0.383*	1					
5.Specialized management software intensity	0.623*	0.733*	0.700*	0.782*	1				
6.Cloud computing	0.274*	0.224*	0.305*	0.332*	0.399*	1			
7.e-commerce	0.154*	0.266*	0.189*	0.270*	0.312*	0.157*	1		
8.Webpage	0.078*	0.247*	0.116*	0.175*	0.220*	0.036*	0.208*	1	
9.Social Networks (d)	0.243*	0.143*	0.156*	0.166*	0.245*	0.162*	0.206*	0.071*	1

Variables	1	2	3	4	5	**6**	**7**	**8**	**9**
1. Specialized management software intensity	1000								
2. ICT investment (d)	0.177*	1000							
3.ICT training (d)	0.204*	0.003	1000						
4.Firm age	0.185*	0.072*	0.124*	1000					
5.# employees	0.220*	0.037*	0.097*	0.127*	1000				
6.Sales (log)	0.646*	0.189*	0.196*	0.240*	0.380*	1000			
7.Export (d)	0.278*	0.102*	0.109*	0.200*	0.091*	0.388*	1000		
8.Foreign ownership (d)	0.227*	0.057*	0.046*	0.026	0.126*	0.278*	0.289*	1000	
9.% employees with a bachelor degree	0.222*	0.020	-0.110*	-0.011	-0.008	0.203*	0.141*	0.200*	1000

*** p<0.01, ** p<0.05, * p<0.1

Source: Author calculations based on ELE 3-4-5, INE.

Appendix Table 10. Pairwise correlations - Ecuadorian firms

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Cloud computing (d)	1000												
2. e-commerce (d)	0.168*	1000											
3.Web with DC (d)	0.176*	0.223*	1000										
4.Fast broadband (d)	0.106*	0.078*	0.133*	1000									
5.Social network (d)	0.167*	0.171*	0.257*	0.094*	1000								
6.CRM	0.142*	0.188*	0.171*	0.052*	0.187*	1000							
7.OCM	0.151*	0.219*	0.121*	0.041*	0.138*	0.424*	1000						
8.SCM	0.141*	0.177*	0.124*	0.037*	0.134*	0.337*	0.556*	1000					
9.FBM	0.169*	0.168*	0.152*	0.052*	0.162*	0.366*	0.416*	0.530*	1000				
10.HRM	0.189*	0.161*	0.169*	0.069*	0.190*	0.360*	0.384*	0.480*	0.636*	1000			
11.SSS	0.178*	0.219*	0.169*	0.070*	0.216*	0.405*	0.473*	0.455*	0.457*	0.460*	1000		
12. SPM	0.163*	0.159*	0.150*	0.061*	0.168*	0.283*	0.352*	0.396*	0.379*	0.398*	0.438*	1000	
13. KM	0.191*	0.182*	0.175*	0.098*	0.202*	0.307*	0.298*	0.312*	0.358*	0.389*	0.390*	0.503*	1000

Variables	1	2	3	4	5	6	7	8	9
1. Specialized management software intensity	1000								
2. CRM	0.606*	1000							
3.OCM	0.698*	0.424*	1000						
4.SCM	0.727*	0.337*	0.556*	1000					
5.FBM	0.730*	0.366*	0.416*	0.530*	1000				
6.HRM	0.728*	0.360*	0.384*	0.480*	0.636*	1000			
7.SSS	0.732*	0.405*	0.473*	0.455*	0.457*	0.460*	1000		
8.SPM	0.693*	0.283*	0.352*	0.396*	0.379*	0.398*	0.438*	1000	
9.KM	0.656*	0.307*	0.298*	0.312*	0.358*	0.389*	0.390*	0.503*	1000

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Cloud computing (d)	1000																
2. e-commerce (d)	0.168*	1000															
3.Web with DC (d)	0.176*	0.223*	1000														
4.Fast broadband (d)	0.106*	0.078*	0.133*	1000													
5.Social Network (d)	0.167*	0.171*	0.257*	0.094*	1000												
6.ICT investment (d)	0.116*	0.129*	0.178*	0.036*	0.148*	1000											
7.ICT training (d)	0.159*	0.148*	0.207*	0.103*	0.172*	0.190*	1000										
8.Network intensity use	0.189*	0.178*	0.295*	0.097*	0.211*	0.226*	0.267*	1000									
9.Specialized management software intensity	0.238*	0.264*	0.220*	0.087*	0.251*	0.199*	0.241*	0.301*	1000								
10.Firm age	0.067*	0.061*	0.149*	0.043*	0.104*	0.151*	0.163*	0.167*	0.104*	1000							
11.# employees	0.074*	0.028*	0.127*	0.112*	0.097*	0.155*	0.199*	0.188*	0.119*	0.204*	1000						
12. Sales (log)	0.127*	0.076*	0.161*	0.056*	0.112*	0.280*	0.248*	0.293*	0.235*	0.254*	0.492*	1000					
13. Machinery (log)	0.009	0.003	0.012	0.010	0.009	0.018*	0.028*	0.017	0.013	-0.001	0.164*	0.074*	1000				
14. Inputs (log)	0.022*	-0.005	0.033*	0.027*	0.022*	0.046*	0.066*	0.059*	0.047*	0.060*	0.344*	0.206*	0.075*	1000			
15. % employees who are professionals	0.069*	0.046*	0.119*	0.096*	0.083*	0.090*	0.112*	0.116*	0.033*	0.067*	-0.015	-0.048*	-0.005	-0.019*	1000		
16. Export (d)	0.094*	0.081*	0.092*	0.006	-0.017	0.109*	0.111*	0.139*	0.133*	0.124*	0.121*	0.288*	0.023*	0.101*	-0.019*	1000	
17. Foreign owenrship (	0.092*	0.062*	0.097*	0.026*	0.012	0.129*	0.106*	0.176*	0.111*	0.082*	0.084*	0.246*	0.000	0.045*	0.036*	0.256*	1000

*** p<0.01, ** p<0.05, * p<0.1

Source: Author calculations based on ENESEM 2016-2022, INEC

Appendix Table 11. Pairwise Correlations: Colombian Manufacturing Firms

Variables	1	2	3	4	5	6	7
1. AI	1						
2. Cloud comptuing	0.220*	1					
3. e-commerce	0.030*	0.0058*	1				
4. Web	0.088*	0.171*	0.099*	1			
5. Social netwroks	0.111*	0.165*	0.104*	0.415*	1		
6.Network intensity use	0.185*	0.269*	0.092*	0.262*	0.227*	1	
7.Specialized management software intensity	0.328*	0.415*	0.114*	0.242*	0.233*	0.453*	1

Variables	1	2	3	4	5	6	7	8
1. Age	1							
2. Size	0.287*	1						
3. % employees with a bachelor degree	0.082*	0.039*	1					
4. Sale	0.178*	0.405*	0.115*	1				
5. Capital	0.126*	0.229*	0.048*	0.592*	1			
6. Material	0.127*	0.278*	0.097*	0.968*	0.079*	1		
7. Export	0.174*	0.273*	0.135*	0.120*	0.095*	0.262*	1	
8. FDI	0.209*	0.272*	0.171*	0.156*	0.069*	0.095*	0.262*	1

*** p<0.01, ** p<0.05, * p<0.1

Source: Author calculations based on ENTIC 2019-2020, Dane.

Appendix Table 12. Pairwise Correlations: Colombian Retail and Wholesale Firms

Variables	1	2	3	4	5	6	7
1. AI	1						
2. Cloud computing	0.235*	1					
3. e-commerce	0.032*	0.074*	1				
4. Web	0.098*	0.231*	0.162*	1			
5. Social networks	0.096*	0.184*	0.141*	0.526*	1		
6.Network intensity use	0.164*	0.258*	0.102*	0.379*	0.331*	1	
7.Specialized management software intensity	0.315*	0.419*	0.104*	0.365*	0.302*	0.437*	1

Variables	1	2	3	4	5	6
1. Age	1					
2. Size	0.097*	1				
3. Capital	0.060*	0.758*	1			
4. Intermediate consumption	0.091*	0.875*	0.702*	1		
5. % employees with a bachelor's degree	0.084*	-0.019	0.031	0.078*	1	
6. Sales	0.081*	0.846*		0.927*	0.068*	1

*** p<0.01, ** p<0.05, * p<0.1

Source: Author calculations based on ENTIC 2019-2020, Dane.

Appendix Table 13. Pairwise Correlations: Colombian Service Firms

Variables	1	2	3	4	5	6	7
1. AI	1						
2. Cloud computing	0.255*	1					
3. e-commerce	0.052*	0.052*	1				
4. Web	0.101*	0.159*	0.070*	1			
5. Social networks	0.105*	0.150*	0.071*	0.156*	1		
6.Network intensity use	0.182*	0.234*	0.080*	0.053*	0.192*	1	
7.Specialized management software intensity	0.341*	0.390*	0.086*	0.095*	0.199*	0.371*	1

Variables	1	2	3	4	5	6
1. Age	1					
2. Size	0.025*	1				
3. % employees with a bachelor degree	0.033*	-0.021	1			
4. Sales	0.013	0.335*	0.096*	1		
5. Capital	0.001	0.012	-0.005	0.216*	1	
6. Service costs	0.007	0.195*	0.110*	0.760*	0.009	1

*** p<0.01, ** p<0.05, * p<0.1

Source: Author calculations based on ENTIC 2019-2020, Dane.