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Information and Communication Technology (ICT) Investment Determinants

The case of the Colombian manufacturing industry, 2012–2023

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Abstract. This thesis analyses the determinants of ICT equipment investment in Colombian manufacturing establishments using establishment-level panel data from DANE's Annual Manufacturing Survey (EAM) spanning 2012-2023. Grounded in the Resource-Based View and Dynamic Capabilities Theory, it examines how establishment size, labour productivity, export orientation, and human capital composition are associated with ICT equipment investment intensity. The 2012-2023 period is used to document trends and patterns of ICT equipment investment across Colombian manufacturing; the estimation of dynamic associations relies on a System Generalized Method of Moments (System GMM) estimator applied to the 2018-2023 sub-period, for which complete and consistent data are available across all regressors. A complementary classification of establishments as active or inactive ICT investors is proposed as a direction for future research. The findings aim to inform digital transformation policy in emerging economies.

Keywords: ICT investment; System Generalized Method of Moments (System GMM); Resource-Based View; Dynamic Capabilities; Manufacturing sector; Longitudinal analysis.

Table of Contents

1. Introduction 4
2. Literature Review 9
   2.1. Empirical Evidence 9
   2.2. Theoretical Framework 12
      2.2.1. Resource-based View of the firm 12
      2.2.2. Dynamic Capabilities Theory 13
3. Methodology & Empirical Strategy 14
4. Data 19
   4.1. Data limitations 20
   4.2. Descriptive statistics 22
5. Results & Discussion 25
6. Robustness checks 30
   6.1. Difference GMM and no-2023 dummy 30
   6.2. Attrition analysis 32
   6.3. Scale-adjusted ICT equipment investment measures 34
   6.4. Heterogeneity analysis –Size 36
7. Conclusions 37

References 38

Appendix 42

1. Introduction

Colombia's manufacturing sector represents a vital component of the national economy, contributing approximately 10% to GDP (World Bank, 2025) and employing around 2.6 million people (DANE, 2026). The sector has undergone significant structural transformation since 2008, facing persistent challenges including real exchange rate appreciation, increased competition from China, and trade disruptions with Venezuela (Griffin, 2015). Manufacturing value-added expanded from US$13 billion to US$36 billion between 2003 and 2021, positioning Colombia as the fifth largest manufacturing economy in Latin America and the Caribbean (ProColombia, 2024). Nonetheless, compared to eight Latin American peers[1], Colombia's manufacturing value-added as a share of GDP ranks seventh, and, as Figure 1.1 shows, a generalized downward trend in manufacturing's GDP share has been observed across Latin American countries since at least the mid-1970s. Colombia's manufacturing sector GDP share has declined approximately 14 percentage points from 24% in 1976 (Figure 1.1; World Bank, 2025).

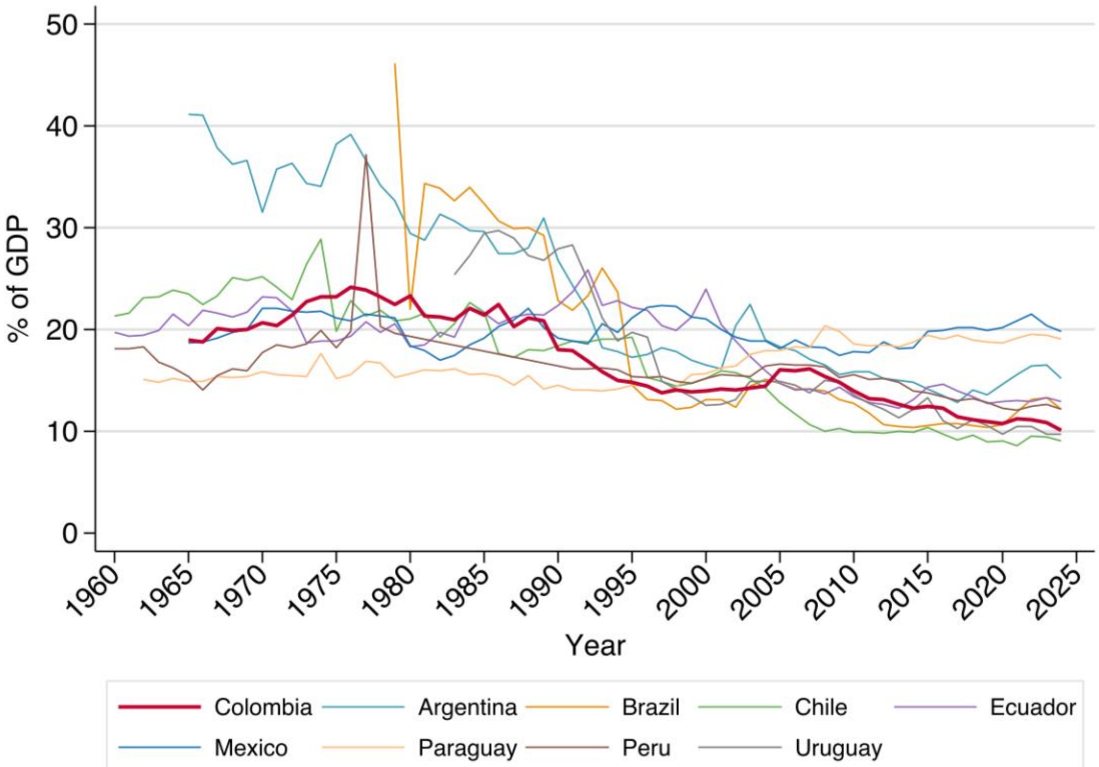
In this context, ICT investment is widely regarded in the economic literature as an important contributor to firm-level productivity and competitiveness (Gallego et al., 2024). This makes the determinants of ICT investment a relevant object of study, particularly in a manufacturing sector facing sustained competitive pressures. Colombia's aggregate position in this regard is modest: ICT investment as a share of GDP stood at approximately 1.6% in 2023, down nearly 0.7 percentage points from its peak of around 2.3% in 2006 –well below Belgium's 3.5% and the OECD average of approximately 2.9%, though exceeding Mexico's roughly 1.3% (Figure 1.2; OECD, 2025). Colombia's figures for 2005-2013 capture ICT equipment only, as software investment data are unavailable for that period, meaning the observed decline from the 2006 peak may understate the true gap if software investment was significant at that time. Although services firms appear to benefit from ICT to a greater extent than manufacturing firms (Aboal & Tacsir, 2018), understanding what determines ICT equipment investment in manufacturing remains important, both because it is a precondition for any policy that seeks to use ICT as a development tool, and because the evidence base for this question in Colombian manufacturing remains limited. The EAM captures investment in ICT fixed assets (computing and communications equipment) as a monetary flow at the establishment level over a sustained period, providing the data infrastructure necessary for longitudinal analysis of ICT equipment investment determinants in Colombia, a data advantage the Annual Services Survey (EAS), which records ICT use and e-commerce activity but not investment values, does not offer

During the 2012-2023 period there were multiple events and policies that may have altered ICT investment trends among manufacturing establishments. Table 1.1 summarizes the most relevant. Though pre-2012, Law 1341 of 2009 –called the ICT Law– set forth the general framework ICT public policy, created FonTIC, a fund oriented to financing plan, programs and projects to facilitate primarily universal access and service of all the inhabitants of the national territory to the Information and Communications Technologies (art. 34). Probably the single most important event for ICT investment during the 2012-2023 period is the COVID-19 pandemic in 2020, which prompted a subsequent increase in ICT investment as a share of GDP in Colombia in 2021 (Figure 1.2). The same pattern arises when looking at mean

[1] The list of countries chosen for this comparison is based on the list of countries used by the The SME Policy Index: Latin America and the Caribbean 2024 (OECD/CAF/SELA, 2024).

ICT investment throughout the entire 2012-2023 period (Figure 1a).

Figure 1.1. Manufacturing Value Added (% of GDP)
Colombia and Latin American Peers



Source: World Bank (2025), World Development Indicators, Manufacturing value added (% of GDP). Retrieved from https://databank.worldbank.org/reports.aspx?source=2&series=NV.IND.MANF.ZS&country=COL

Understanding the determinants of ICT investment is crucial for several reasons. First, it helps identify barriers and facilitating factors that influence firms' decisions to invest in digital technologies. Second, it contributes to the broader literature on technology adoption and establishment-level investment decisions in developing countries, with particular relevance for understanding how digital transformation occurs across different establishment sizes and sectors. Finally, it provides insights for policymakers seeking to design effective interventions to promote technological adoption and digitalization.

While the existing literature has extensively studied the effects of ICT on business productivity and performance, as well as ICT adoption, much less attention has been paid to understanding what drives businesses to invest in ICT in the first place, using longitudinal analysis. This research gap is particularly pronounced in emerging economies, where institutional, infrastructure and market conditions differ substantially from those in developed countries. Recent studies have also highlighted the importance of complementary factors in ICT adoption in high-income countries. For instance, the 2025 OECD D4SME Survey[2] reveals

[2] The countries surveyed were Australia, Canada, France, Germany, Italy, Japan, Korea, Spain, the United

that while 58% of SMEs use digital financial services, only 28% track environmental data using digital tools, suggesting significant variation in digital technology adoption across different business functions (Bianchini & Lasheras Sancho, 2025). The literature on ICT in developing countries has identified several key factors. Research by Aboal and Tacsir (2018) using Uruguayan data found that ICT plays a bigger role for innovation and productivity in services than in manufacturing, suggesting sector-specific heterogeneity in ICT effects. Similarly, studies from Iberoamerica by Guzman et al. (2016) demonstrate positive relationships between innovation activities and ICT usage, as well as between ICT adoption and business performance in SMEs. Gallego and Gutiérrez (2015) analyse data on ICT in firms in Latin America and the Caribbean (LAC) between 2002 and 2013 for most countries. Regarding the adoption and use of ICT, the authors note that the analysed data suggest that both measures increase with firm size and decrease with the complexity of ICT (Gallego & Gutiérrez, 2015).

Table 1.1. Events, Policies & Regulatory Changes and its Impact on ICT Investment (2012-2023)

Event, Policy or Regulatory change	Year	What it did	Importance to manufacturing ICT investment
Law 1607 of 2012 (tax reform)	2012	Established a tax exclusion – no VAT– for computers and mobile devices below a price threshold.	Reduced the cost of ICT hardware for both firms and households. Potentially key for smaller manufacturers.
Law 1819 of 2016 (tax reform)	2016	Restructured the science, technology and innovation tax incentives regime by introducing a 25%-30% tax discount for qualified R&D/innovation.	Directly impacts firms' technology and innovation CAPEX through a fiscal channel.
Law 1955 of 2019 – National Development Plan (Plan Nacional de Desarrollo)	2019	Included provisions for the Fourth Industrial Revolution, a public investment plan and a 50% fiscal credit for MSMEs R&D investment.	It established the legal framework for spending in digital transformation.
Spectrum Auction (December of 2019)	2019	Modernized the network from 2G/3G to 4G.	Impacted the connectivity price and quality.
COVID-19 pandemic	2020-2021	Demand shock to ICT use and investment due to nationwide lockdowns.	Forced firms to quickly implement digitization plans or to go fully digital.
Law 2277 of 2022 (tax reform)	2022	Modified the fiscal-incentive structure for R&D/innovation investment.	Impacts firms' technology and innovation investments.

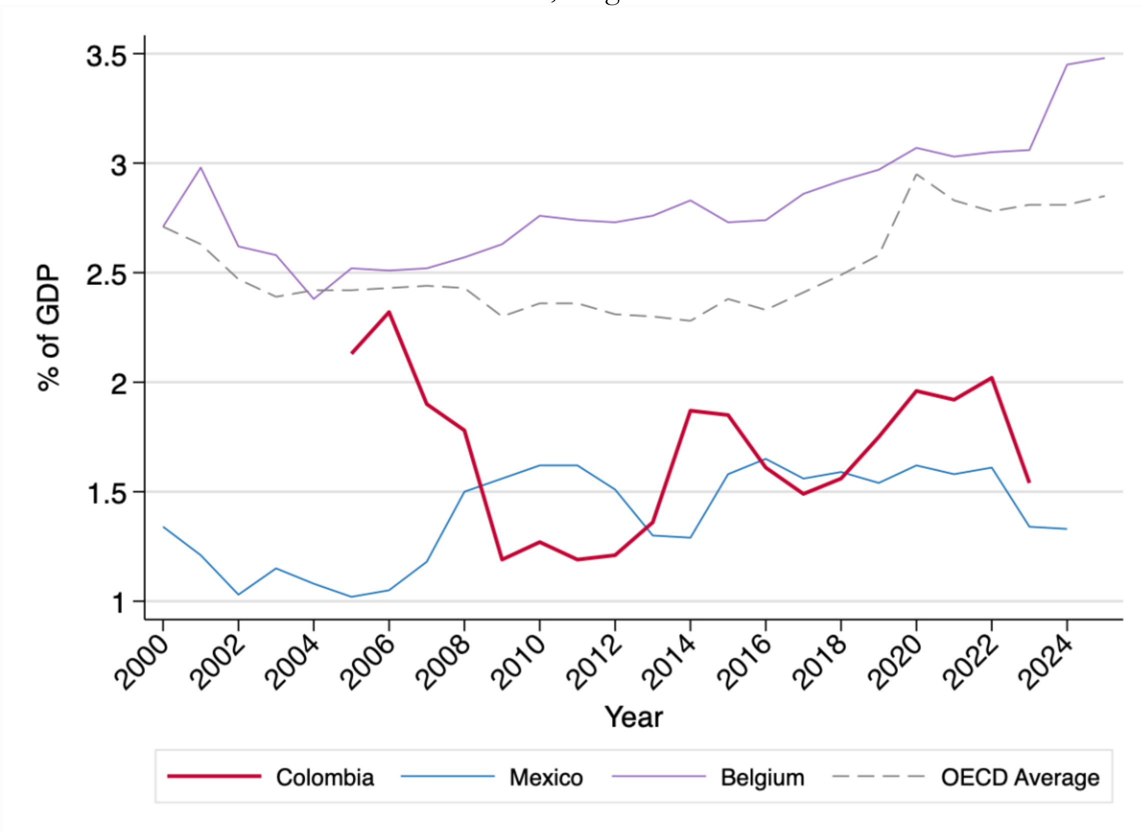
Note. Chronology of selected events, policies and regulatory changes potentially affecting ICT investment, 2012-2023. Source: own elaboration based on the cited legal and policy sources.

Therefore, they propose a pattern of ICT adoption that generally applies to firms in the LAC region, namely, that smaller firms adopt and use basic ICTs, while large firms and more advanced SMEs exhibit greater use of complex ICTs like intranet, extranet, CRM's and cloud

Kingdom, and the United States.

computing (Gallego & Gutiérrez, 2015). This finding is consistent with the results obtained through a literature review of ICT adoption by SMEs in developing countries carried out by Díaz-Arancibia et al., (2024), who find that digital transformation is primarily about integrating basic ICTs.

Figure 1.2. ICT Investment (% of GDP)
Colombia vs. Mexico, Belgium and the OECD



Note: Own calculations based on OECD (2025), OECD Going Digital Toolkit (Indicator 30), ICT Investment (% of GDP). Retrieved from https://goingdigital.oecd.org/indicator/30.
ICT investment = ICT equipment + computer software & databases (excl. IP and R&D).
Colombia 2005-2013: ICT equipment only (software data unavailable).

The SME Policy Index: Latin America and the Caribbean 2024 constructed by the OECD, the Development Bank for Latin America and the Caribbean –CAF and the Latin American and Caribbean Economic System –SELA (2024), provides valuable contextual measurements for the region with data on nine countries, namely, Argentina, Brazil, Paraguay, Uruguay, Chile, Colombia, Mexico, Peru and Ecuador. The SME Policy Index assigns a score on a scale from 1 to 5, with 5 being the highest.[3] For instance, on the digitalisation dimension of SMEs Colombia ranks below the average (4.16) of the nine countries with a score of 3.96. Top performers on this dimension are Chile, Brazil, Uruguay and Mexico, all of which score higher than the average of 4.16.[4] The digitalisation dimension is comprised by three sub-dimensions: (i) National Digital Strategy, (ii) broadband connectivity, and (iii) digital skills. On these three

[3] OECD/CAF/SELA, 2024.
[4] OECD/CAF/SELA, 2024.

sub-dimensions Colombia scores 4.80, 3.94 and 3.13, compared to the averages of 4.57, 3.98 and 3.92, respectively. Interestingly, Colombia's score on digital skills is the second lowest (3.13) of the nine countries analysed by the SME Policy Index, outperforming only Argentina (3.03) and well below Chile (4.73), the top performer in this regard OECD/CAF/SELA, 2024). This could help explaining low take-up rates for digital business training interventions in micro enterprises, as documented by Rodríguez-Lesmes et al. (2025). Furthermore, regarding the use of e-commerce as a sub-dimension of Access to market and internationalisation, Colombia scores 3.90, just below of the average for the nine countries in the sample (3.99), and below the top performers: Uruguay (4.46), Brazil (4.30), Mexico (4.26), and Chile (4.17) (OECD/CAF/SELA, 2024). This presents a rough picture of Colombia's highs and lows with respect to digitalisation of SMEs, reinforcing the idea that there's still work to do to better understand what contributes and facilitates the digital transformation among SMEs.

Previous studies on Colombian manufacturing firms have primarily focused on ICT adoption patterns using cross-sectional data. Notably, Gallego, Gutiérrez, and Lee (2015) analysed ICT adoption determinants among 3,759 Colombian manufacturing firms using data from the 2006 EAM, finding that human capital, organizational changes, and innovation activities were key facilitators of ICT adoption. However, their study examined ICT adoption (binary decisions) rather than investment levels and used only cross-sectional data from a single year. Furthermore, research on digital business training interventions among Colombian microentrepreneurs shows that take-up rates for digital technologies remain challenging, even with local promotion efforts (Rodríguez-Lesmes et al., 2025).

This research differs fundamentally from previous work in several key aspects. First, it places the focus on ICT investment versus adoption. While prior studies examined whether firms adopt ICT, this research analyses the determinants of ICT equipment investment intensity which is a continuous variable (measured in real COP thousands, deflated to constant 2018 prices). Second, it performs a longitudinal analysis. This study employs panel data spanning 12 years (2012-2023) versus single-year cross-sectional analysis. Third, it uses establishment-level granularity. The analysis is conducted at the establishment level rather than firm level, potentially providing more precise insights. Lastly, it employs a comprehensive temporal coverage, as it captures various economic cycles, policy changes, and technological evolution over a twelve-year period. This paper studies the determinants of ICT investment in Colombian manufacturing firms at establishment-level between 2012 and 2023. We also document trends and patterns of ICT investment across Colombian manufacturing establishments from 2012 to 2023. This is done by employing System Generalized Method of Moments –System GMM approach, under the assumption that there are no good exogenous instruments to address endogeneity concerns (See Section 3 for a discussion).

The main findings can be summarized as follows. Establishment size emerges as the only determinant of ICT equipment investment that is statistically significant at conventional levels, with an elasticity greater than one, consistent with the view that larger establishments command the financial resources and scale needed to invest more intensively in computing and communications equipment. The remaining establishment characteristics, namely, labour productivity, export orientation, and human capital composition, are not statistically significant in the System GMM specification; as the variance decomposition shows, this reflects the limited within-establishment variation in these variables over the estimation period rather than evidence of no association. The estimated dynamic term is imprecise, consistent with an intermittent rather than strongly persistent pattern of ICT equipment investment, a pattern expected for durable capital goods that are acquired periodically rather than continuously. Taken together, these results suggest that, for most establishments in this predominantly small and medium-sized, low-technology-intensity sector, ICT equipment investment does not yet appear to function as a strategic resource in the sense of the Resource-Based View, nor as a foundation for dynamic capabilities in the sense of Teece et al. (1997).

The rest of this document is organized as follows. Section 2 presents a review of literature and introduces the theoretical framework. Section 3 presents the methodology and the empirical strategy. Section 4 presents the data used and descriptive statistics. Section 5 introduces the estimation results and discusses them. Section 6 presents some robustness checks. Finally, Section 7 concludes, presents policy implications and possible areas for future research.

2. Literature Review

2.1. Empirical Evidence

The literature on ICT adoption and investment in manufacturing has evolved significantly, with early studies focusing on binary adoption decisions and more recent work examining investment intensity and heterogeneous effects. Table 2.1 presents a summary of the most relevant studies for this research. Aboal and Tacsir (2018) provide important insights through their CDM-model analysis, demonstrating that ICT plays different roles across sectors, with particularly strong effects in services compared to manufacturing. Their findings suggest that the complementarity between ICT and other factors varies substantially across industries, reinforcing the need for sector-specific analysis. The authors' results demonstrate that while traditional R&D represents a small portion of innovation investment in developing countries, other innovation activities (including ICT investment) play more prominent roles. This finding is particularly relevant for understanding ICT investment patterns in Colombian manufacturing, where firms may rely more on technology acquisition and adaptation rather than internal R&D.

International evidence on ICT investment determinants comes from Bianchini and Lasheras Sancho (2025), who analysed SME digitalization patterns across 10 OECD high-income countries using the D4SME Survey.[5] Their study identifies key barriers to digital adoption including lack of digital skills, insufficient financial resources, and organizational resistance. Importantly, they find that firm size, sector, and country-specific factors significantly influence digitalization decisions, suggesting that national context matters substantially for understanding ICT investment patterns.

The complexity of digital adoption is further illustrated by Rodríguez-Lesmes et al. (2025) in their randomized controlled trial of digital training for Colombian microentrepreneurs. Despite using local promoters to increase take-up, the intervention only increased app adoption by 3.97 percentage points, with no significant impacts on financial inclusion, formalization, or business practices. This research provides important context for

[5] The countries included in the survey were Australia, Canada, France, Germany, Italy, Japan, Korea, Spain, the United Kingdom, and the United States.

understanding ICT adoption barriers in Colombia, particularly for smaller establishments. The authors note that "microentrepreneurs frequently cite lack of time, low motivation, and distrust in external programs as key reasons for their reluctance to engage with training content." These findings suggest that ICT investment decisions may be influenced by similar behavioural and institutional factors beyond purely economic considerations.

Table 2.1. ICT and Firms: Empirical evidence

Study	Context	Method	ICT measure	Key finding
Gallego, Gutiérrez & Lee (2015)	Colombian manufacturing firms	Seemingly unrelated regression (SUR) model with cross-section data	ICT adoption	Human capital, organizational changes, product or process-related innovation and spillover effects of previous ICTs are key to new ICT adoption.
Aboal & Tacsir (2018)	Uruguayan services and manufacturing firms	Crépon, Duguet and Mairesse (CDM)-type three-stage model	ICT adoption & ICT investment per worker	Firm size and human capital drive both the decision to invest and the level of investment in ICT.
Gallego Acevedo, Nieves, Vargas, Díaz, & Saboin (2024)	Colombian manufacturing firms	Augmented production function (control function approach –GMM)	ICT capital stock	Highly heterogenous returns by firm size, technological intensity, innovation status and export orientation.
Cataldo, Pino & McQueen (2020)	Chilean MSMEs	Cobb-Douglas production function	Combinations of ICT assets (software applications) on firm performance	No cost reduction effect from the use of ICT assets. However, the higher the ICT adoption maturity stage of the firm, the greater the impact of ICT assets on sales revenue and profitability (ROA)

Note. Summary of selected empirical studies on ICT investment and firm performance. Source: own elaboration.

Regional evidence from Latin America is provided by Guzman et al. (2016), who surveyed 1,989 SMEs across 21 Iberoamerican countries. Their study confirms positive relationships between innovation activities, ICT usage, and firm performance, while identifying significant cross-country variation in adoption patterns and determinants.

The most directly relevant study for Colombian manufacturing is Gallego et al. (2015), which analysed determinants of ICT adoption using data from the 2006 EAM. Their cross-sectional analysis identified firm size, export intensity, and technological capability as key predictors of ICT adoption. However, their study was limited to a single year and focused on binary adoption rather than investment intensity and a longitudinal analysis.

Recent work by Gallego et al. (2024) complements this earlier research by examining the productivity effects of ICT capital from 2013-2018. Using an augmented production function approach estimated through GMM, with the value of production as their dependent variable, they find that ICT capital contributes significantly to output with elasticities comparable to non-ICT capital and labour. Across all specifications, the elasticity of ICT capital ranged from 0.015 to 0.029, meaning that a 1% increase in ICT capital is associated with a 0.015% to 0.029% increase in output (measured as a function of technological progress –or TFP in the paper's context–, capital, and labour). Crucially, their results reveal substantial heterogeneity: innovative, high-tech, exporting, and larger firms exhibit higher output elasticities of ICT capital than their non-innovative, low-tech, non-exporting, and smaller counterparts, as summarized in Table 2.2.

The size of these gaps is as telling as their direction. The elasticity for high-tech firms is roughly fourteen times that of low- and medium-tech firms, and the effect among non-innovative firms cannot be distinguished from zero, indicating that the returns to ICT capital depend heavily on the firm's technological and innovative base rather than on ICT investment alone. This heterogeneity underscores the crucial role of firm capabilities and sectoral characteristics as complements to ICT investment.

Of particular relevance to this study are the findings regarding firms' level of ICT investment in relation to their output. As the bottom two rows of Table 2.2 show, the returns to ICT capital rise sharply with investment intensity: firms in the top half of the ICT investment distribution display an elasticity roughly four times that of firms in the bottom half (0.137 versus 0.034), and the gap widens further at the quartile extremes, where the bottom quartile's effect is statistically indistinguishable from zero. This pattern suggests that the productivity payoff from ICT capital is concentrated among firms that invest the most, reinforcing the importance of investment intensity rather than mere adoption.

Table 2.2. Heterogeneity in the output elasticity of ICT capital (Gallego et al., 2024)

Firm characteristic	Elasticity	Counterpart	Elasticity
Innovative	0.088	Non-innovative	Not significant
High-tech	0.758	Low- and medium-tech	0.054
Exporting	0.081	Non-exporting	0.068
Top 50% ICT investment	0.137	Bottom 50% ICT investment	0.034
Top 25% ICT investment	0.165	Bottom 25% ICT investment	Not significant

Note: Each value is the estimated output elasticity of ICT capital, i.e., the percentage change in output associated with a 1% increase in ICT capital, holding other factors constant. Estimates correspond to the KLEMS capital method with GMM (specification 7).

Griffin (2015) provides crucial context for understanding the Colombian manufacturing sector's evolution during the study period. Using firm-level data from 2000-2012, the study identifies a structural break around 2008 related to trade disruption with Venezuela and increased competition from China. The research finds that while real exchange rate appreciation affected export-intensive companies, structural changes partially explain manufacturing sector weakness since 2008. These findings suggest that ICT investment patterns may have shifted significantly during the study period, potentially due to changing competitive pressures and market conditions.

Cataldo et al. (2020) study the impact of different combinations of ICT assets (software applications) used by 5519 Chilean MSMEs in 2009. Thus, they look at firms' ICT maturity stages depending on the combination of software applications used, and its impact on firm performance measured in efficiency and profitability by estimating sales revenue on assets, costs on assets and ROA. They find no cost reduction effect from the use of ICT assets. However, their results indicate that the higher the ICT maturity stage of the firm, the greater the impact of ICT assets on sales revenue and profitability (ROA). Their results also show a great moderating effect of firm size on the effect of ICT assets combination in relation to performance indicators. That is, micro firms with *intermediate* and *advanced* levels of ICT combinations had the highest sales revenues, while small enterprises with *advanced* levels of ICT combinations had an increase in sales revenues. This effect was absent for medium size enterprises.

Across the referenced studies firm size appears consistently and positively associated with ICT investment or adoption, although each one focuses and measures different things. For instance, Gallego et al. (2015) find that larger firms are more likely to adopt ICT. Aboal and Tacsir (2018) find that firm size is positively associated to the decision to invest in ICT both for the services and manufacturing sectors. Finally, Gallego's et al. (2024) results show that bigger firms obtain higher ICT capital elasticities than SMEs. Human capital is also consistent in all, but one: Gallego et al. (2024) do not examine human capital as an ICT investment driver. Nonetheless, Gallego et al. (2015) do identify human capital as one of the main complementary factors that influence ICT adoption by firms.[6] Aboal and Tacsir (2018) find that human capital (as the share of professionals and technicians in the workforce) is important when deciding whether to invest in ICT. Particularly, they find that a doubling of the skilled labor share is associated with a 27.4 percentage point increase in the probability of investing in ICT for manufacturing firms.

The referenced works focus on ICT adoption decisions, ICT investment per worker, and output elasticities of ICT capital stock, using cross-sectional, pooled cross-sections, and panel data. This research differs in two key respects. First, it examines ICT equipment investment as a continuous monetary flow rather than a binary adoption decision, capturing intensity rather than incidence. Second, it employs a dynamic panel specification over the 2018-2023 sub-period, which spans the COVID-19 shock and recovery, using System GMM to address endogeneity and establish evidence suggestive of dynamic associations between establishment characteristics and ICT investment intensity. To the best of my knowledge, this approach has not yet been applied to the Colombian manufacturing sector.

2.2. Theoretical Framework

2.2.1. Resource-based View of the firm

The resource-based theory aims to explain the motives behind a firm's competitive advantage from the perspective of the resources the firm has, as opposed to market dynamics and industrial organization. This theory has been developed, among others, by Wernerfelt (1984), Barney (1986, 1991) and Peteraf (1993). They explain what is needed for a resource to have the potential to generate a sustained competitive advantage. Thus, resources must have four attributes: **(i)** valuable; **(ii)** rare; **(iii)** imperfectly imitable and; **(iv)** non-substitutable.

A resource is valuable when it enables a firm to conceive of or implement strategies that improves its efficiency and effectiveness. For a valuable resource to be rare means that not many firms have that resource or bundle of resources and, therefore not a lot of firms will be able to conceive of and implement the strategies in question that would lead to sustained competitive advantage. Hence, those strategies will not be a source of competitive advantage, even if the resources are valuable. Lastly, a valuable and rare resource is imperfectly imitable

[6] The authors make the distinction between college educated employees and technicians and find that the impact of "…the variable *college* (percentage of workers with a bachelor's degree or higher) appears to have the larger impact on any ICT adoption by firms than the variable *technician* (the ratio of number of technicians to total employees)." (Gallego et al., 2015)

if firms that do not possess it cannot obtain it (Barney, 1991). According to Barney (1991), there are three reasons that explain the imperfect imitability of a resource. First, the ability of a firm to obtain a resource is dependent upon unique historical conditions. Second, the link between the resources possessed by a firm and a firm's sustained competitive advantage is causally ambiguous. This situation creates a difficulty for firms attempting to imitate a successful firm's strategies through imitation of its resource to know which resource it should imitate. Third, the resources generating a firm's advantage is socially complex, meaning that the resource is beyond the ability of firms to systematically manage and influence it. Finally, a resource is said to be non-substitutable when there are no strategically equivalent valuable resources that are themselves either not rare or imitable, because otherwise would mean that the resource cannot be a source of a sustained competitive advantage.

2.2.2. Dynamic Capabilities Theory

Developed by Teece et al. (1997) as an extension of the resource-based view of the firm for dynamic markets (Dejardin et al., 2023; Eisenhardt & Martin, 2000), "dynamic capabilities were defined as the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece, 2018), or as Eisenhardt and Martin (2000) define them:

> "The firm's processes that use resources –specifically the processes to integrate, reconfigure, gain and release resources– to match and even create market change. Dynamic capabilities thus are the organizational and strategic routines by which firms achieve new resource configurations as markets emerge, collide, split, evolve, and die" (p. 1107).

The dynamic capabilities theory aims to explain "…firm survival (or failure) and long-run growth and prosperity – by detailing how firms can create, extend, integrate, modify, and deploy their resources while simultaneously managing competitive threats and effectuating necessary transformations (Teece, 2010a, as cited in Teece, 2025). In this sense, "[D]ynamic capabilities are how the firm determines the resources (including capabilities) and business model(s) it needs for the future" (Teece, 2025).

Teece (2025) mentions three clusters of primary high-order capabilities: **(i)** sensing; **(ii)** seizing and; **(iii)** transforming (p. 7). Sensing refers to the "identification and assessment of threats, opportunities, and customer needs…". On the other hand, seizing comprises the "…mobilization of resources to address fresh opportunities while capturing value from doing so…". Finally, transforming is just ongoing organizational renewal. Having those three capabilities are a condition for firms to create and sustain competitive advantage (Teece, 2025).

Another key feature of dynamic capabilities is that they cannot be easily outsourced or acquired.[7] Rather, firms must invest time and resources in discovery, knowledge generation and learning to build and maintain those capabilities (Teece, 2025).

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[7] In that sense, they resemble the ideas present in the Resource-based View, when it refers to the need of a resource to be valuable, rare, imperfectly imitable and non-substitutable.

Besides sensing, seizing and transforming, authors like Dejardin et al. (2023) propose some additional dynamic capabilities that enhance firms' performance: **(i)** conceptualizing, which is the capability to select and develop an idea; **(ii)** coproducing and orchestrating, which they define as the partnerships established with other organizations in the firm's value chain to retail new products or services; and **(iii)** scaling and stretching, which they understand as the efforts required to get a new product or service to the market.

Following these frameworks, this investigation examines how several establishment-level characteristics (each interpretable through either the RBV or Dynamic Capabilities lens) are associated with investment intensity in ICT equipment in Colombian manufacturing from 2018 to 2023. Establishment size, though interpretable as, it does not fully operates as an RBV resource: larger establishments command greater financial slack, economies of scale, and bargaining power with ICT suppliers, attributes that are valuable, and, in the Colombian manufacturing context where MSMEs predominate, rare and imperfectly imitable. Labour productivity similarly reflects accumulated operational resources and organizational routines that underpin the establishment's capacity to generate and allocate resources toward technology investment. Human capital composition, captured by the share of professional and technical workers and the share of managerial staff, straddles both frameworks: as stocks of knowledge and expertise, these represent VRIN resources in the RBV sense; as enablers of sensing, seizing, and organizational transformation, they also constitute dynamic capabilities in the sense of Teece et al. (1997). Export orientation is interpreted primarily through the Dynamic Capabilities lens: sustaining an export operation requires firms to continuously sense foreign market opportunities, seize them by reconfiguring internal processes, and transform their organizational routines to remain competitive internationally. It should be noted, however, that all variables mentioned may also reflect prior accumulated advantages, in particular, export orientation may reflect aspects such as scale, sectoral structure, or access to international networks, rather than dynamic capabilities per se. The empirical analysis therefore treats these variables as correlates of either valuable resources in light of the RBV or dynamic capabilities developments rather than a direct measure of those concepts, with the direction and magnitude of the association left to the data.

3. Methodology & Empirical Strategy

The main identification strategy employs a two-step System Generalized Method of Moments (System GMM) estimator (Blundell & Bond, 1998) with Windmeijer-corrected robust standard errors (2005)[8], which extends the first-difference GMM estimator of Arellano and Bond (1991) by including an additional set of moment conditions in the levels equation. This approach is appropriate for this study for several reasons.

First, ICT equipment investment likely exhibits persistence over time: establishments that invest in ICT in one year are more likely to do so in subsequent years, making a balanced dynamic panel specification with a lagged dependent variable appropriate. Second, several key regressors, particularly establishment size, productivity and export orientation are likely endogenous, as ICT investment may itself affect them (simultaneity). Thus, we assume the

[8] Windmeijer (2005) found the standard errors of the two-step GMM estimator to be downward biased in small samples, which could inflate t-statistics and lead to spurious rejections of the null hypothesis, making coefficients appear statistically significant when they are not.

absence of good exogenous instruments. This assumption rests on the fact that the covariates or explanatory variables that we rely on in this research's setting are all strictly internal aspects of the same establishment, namely, size, ICT investment, workforce composition, labour productivity, export intensity. This makes finding an external instrument difficult, since any external variable correlated with size, for example, is likely also correlated with ICT investment directly. Hence, all these variables suffer from simultaneity bias, because size affects ICT investment and ICT investment affects size. For instance, as the literature and the results herein show, size has a clear effect on ICT investment, but ICT investment may also enable establishment growth. A good instrument should, therefore, not be correlated with the disturbance term ε_{it} (exogeneity), should have an effect on ICT investment *only* through the endogenous variable (exclusion), say, size (number of employees), and must be strongly correlated with the endogenous variable (relevance). This is why using lagged variables as instruments provided by the GMM approach is useful and appropriate: since the data is serially correlated past values directly impact current and future ones (though the effect fades with more t's), and that same lag structure guarantees that the lagged variables are not correlated with the *current* error term.

System GMM addresses this by using lagged levels and differences of the endogenous variables as internal instruments. While System GMM partially addresses endogeneity, the deep lag structure required for instrument validity comes at the cost of reduced instrument strength, meaning the results should be interpreted as evidence suggestive of dynamic associations rather than clean causal estimates. Third, the relatively short time dimension of the period (6 years) relative to the number of establishments is well-suited to the System GMM framework, which was designed precisely for balanced panels with large N and small T.

This research uses a System of the Generalized Method of Moments (GMM) approach rather than Difference GMM because the lagged levels are weak instruments for first differences when the series is persistent (Blundell & Bond, 1998), as confirmed by the negative Difference GMM coefficient. In addition, as ICT investment is likely persistent at the establishment level, when the autoregressive parameter α is close to one, the series behaves close to a random walk, in which case a problem of weak instruments arises for the lagged levels instrumenting first differences (Blundell & Bond, 1998), and the coefficient on the lagged dependent variable becomes mostly noise. A Difference GMM specification is estimated, providing empirical evidence that supports the methodological choice, as the estimates are expected to be biased downward due to the weak instrument problem documented in the literature on the GMM estimator (Blundell & Bond, 1998; Blundell & Bond 2000; Blundell, Bond & Windmeijer, 2000; Bond, 2002).

Thus, the dynamic specification is motivated by both theoretical and empirical considerations. Theoretically, ICT investment involves sunk costs, installed infrastructure, and organizational routines that create inertia in investment behaviour. Empirically, the pattern of estimates across specifications provides indirect evidence consistent with persistence. The OLS estimator, which is known to produce an upward-biased autoregressive coefficient in dynamic panels (Bond, 2002), yields $\alpha = 0.358$ (significant at 1%), establishing a statistical upper bound. The Difference GMM estimator produces a negative coefficient ($\alpha = -0.206$), which is theoretically implausible and is the classic signature of weak instruments arising precisely when the series is persistent, as Blundell and Bond (1998) document. The System GMM estimate ($\alpha = 0.216$) is positive and lies between the OLS and Fixed Effects bounds, consistent with Bond's (2002) diagnostic criterion for a well-specified dynamic panel estimator. While the System GMM autoregressive coefficient is imprecise and does not reach conventional significance levels, suggesting investment is episodic rather than strongly persistent over this sub-period, the cross-estimator pattern supports including the dynamic term rather than imposing the restriction that $\alpha = 0$.

For the econometric analysis using System GMM, a balanced panel is constructed for the estimation period (2018-2023). Within this period, the balanced panel retains only those establishments observed in all six years. This is a requirement of the System GMM framework, which relies on a complete set of lagged levels and differences as internal instruments; gaps in the panel would invalidate the moment conditions underlying the estimator (Blundell & Bond, 1998; Roodman, 2009). Hence, the estimation is restricted only to the last sub-period (2018-2023, given the missing data for the export variable in 2014, which created gaps in the panel and made the AR(2) test impossible to compute due to the reduction on effective observations per group.

Constructing a balanced panel, rather than requiring presence across all twelve years, mitigates survivorship bias: many establishments that would be excluded from a full-period balanced panel are retained in the sub-period. This is documented in Section 6.2. Nonetheless, the characteristics of balanced versus unbalanced establishments will be documented and compared to assess the degree of selection.

As suggested by Bond (2002) and Roodman (2009), an OLS and an OLS with fixed effects[9] specifications are estimated to exploit their documented upward and downward biases, respectively, and get upper and lower bound benchmark coefficients for α, since the consistent System GMM estimator is expected to lie between the OLS and the fixed effects estimates (Bond, 2002, p. 144). These two specifications are also estimated on the 2018-2023 balanced panel to ensure the same conditions for all estimates and allow for comparability. For the STATA estimation of the System GMM, the `xtdpdgmmn` command developed by Kripfganz (2019) is used instead of `xtabond2`, which was developed by Roodman (2009) due to some bugs related to the treatment of time dummies and the number of available degrees of freedom to compute the AR(2) and Hansen tests, as documented by Kripfganz (2019).

The validity of the System GMM instruments is assessed using the Sargan/Hansen test of overidentifying restrictions and the Arellano-Bond test for second-order serial correlation in the first-differenced residuals (AR(2)). The absence of AR(2) indicates that the differenced error term is not serially correlated at order two, which supports the validity of the lagged levels used as instruments (Roodman, 2009). Since time-invariant regressors such as sector and department dummies are eliminated by the first-difference equation and identified only through the levels equation, limiting the number of such dummies helps preserve the reliability of the Sargan/Hansen test of overidentifying restrictions (Roodman, 2009). The Difference-in-Sargan/Hansen test is also employed to formally assess the validity of the additional moment conditions (Arellano & Bover, 1995; Blundell & Bond, 1998) and gather indirect empirical evidence that supports that the stationarity condition is not violated in the data for the estimated period (2018-2023), because the levels equation instruments, that is, the lagged

[9] Also called the "Within Groups" estimator. (For instance, Blundell & Bond, 1998; and Bond, 2002).

differences that act as instruments for the lagged levels, are valid only if the stationarity assumption holds, whereas the lagged levels acting as instruments for the first differences do not depend on this assumption. So, if the incremental contribution of the lagged differences instrumenting the levels equation is too large, then the levels equation might be the problem indicating that it does not satisfy the stationarity condition. For alternative estimation windows where the standard Difference-in-Sargan/Hansen statistic is not computable due to negative degrees of freedom arising from the deep lag structure, the test is approximated via a restricted model dropping the level-equation GMM blocks while retaining year instruments for identification.

Instrument proliferation will be managed by collapsing the instrument matrix, limiting lag depth and specifying sectoral controls at the 2-digit ISIC level rather than the 4-digit level. The choice to set sector controls at the 2-digit ISIC level has several implications worth discussing further. Thus, some granularity may be lost with respect to sector specific ICT trends, however that trade-off generates two things that are positive for the chosen econometric model, namely, it increases variance across sectors because with less sectors comprising more establishments their densities increase producing larger heterogeneity across industries, and reduces instrument count, which contributes to the avoidance of the instrument proliferation problem. The importance of introducing sector specific control lies in that some sector may be more technology intensive than others and could be a major driver of investment in ICT. To verify the identifying power of the instrument set, an underidentification test following Kleibergen and Paap (2006) will be conducted, and its results will be reported alongside the main estimates.

The baseline dynamic specification is:

$$lnICT_{it} = \alpha lnICT_{i,t-1} + \beta_1 Size_{it} + \beta_2 Productivity_{it} + \beta_3 ExportIntensity_{it} + \beta_4 ProfTech_{it} + \beta_5 Mgmnt_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad \textbf{(3.1)}$$

where $lnICT_{i,t-1}$ is the lagged dependent variable, capturing persistence in ICT investment; μ_i captures establishment fixed effects (time-invariant unobserved heterogeneity); λ_t captures year fixed effects; and ε_{it} is the idiosyncratic error term. Human capital is captured by two components on the equation, namely the share of professional/technical workers and the share of managerial staff, which are treated as predetermined regressors[10] in the model.[11] The

[10] Predetermined variables are those whose values at time *t* are determined outside the system, that is, that are only correlated with the lagged error term, but not with the current error term as endogenous variables are (Dhrymes, 2017, pp. 355-356).

[11] Even though Hamermesh (1993, as referenced in Hamermesh & Pfann, 1996) showed that the adjustment lag for changes to a firm's workforce is significantly shorter than for capital (with employment demand exhibiting a half-life of approximately three to six months) this refers to the speed of adjustment for total headcount. The story is different with regards to workforce composition and, particularly, skilled labor. As Castellani et al. (2020) and Eslava et al. (2014) have shown, skilled workers in the Colombian manufacturing sector are predominantly hired on permanent contracts, which carry high severance and dismissal costs even after the 1990 labor reform (Kugler, 2004; Heckman & Pagés, 2000). And particularly Eslava et al. (2014) show that fixed-term contracts provide greater flexibility. This makes adjusting the skilled workforce costly for firms in both directions: dismissing skilled workers involves foregone firm-specific human capital, while hiring replacements entails substantial search, training, and disruption costs that are significantly higher than for unskilled labor (Ghaly et al., 2017) due to greater flexibility provided by fixed-term contracts, which even became a main shock absorber after the 1990's reforms in Colombia (Eslava et al, 2014). The evidence thus suggests a certain stickiness of skilled

model does not include an initial condition as an explicit regressor for three reasons. First, the initial condition enters the System GMM estimator through the moment conditions that underpin the levels equation under the stationarity assumption (Blundell & Bond, 1998), making an explicit regressor redundant. Second, the lagged dependent variable $lnICT_{i,t-1}$ already captures much of the persistence information that $lnICT_{i,t_0}$ would provide, introducing near-collinearity between the two. Third, including a time-invariant regressor in the levels equation creates additional pressure on the instrument matrix and can exacerbate the instrument proliferation problem (Kripfganz, 2019). The dependent variable, ICT investment, is transformed as $\ln(ICT_{it} + 1)$, where monetary values are expressed in constant 2018 COP thousands. This transformation retains establishments reporting zero ICT investment in a given year, which represent a deliberate choice not to invest rather than missing data, while approximating a logarithmic scale for positive values. Since the added unit corresponds to COP1,000, that is, less than 0.001% of the median ICT investment across all periods, the scale dependence introduced by the transformation is practically negligible (Bellemare & Wichman, 2020). The transformation therefore retains the elasticity-like interpretation of the coefficients for all but the very smallest observations.

A potential limitation of measuring ICT investment in monetary units is that it may mechanically favour larger establishments, even when their underlying technological intensity is similar. In the Colombian manufacturing context, where MSMEs account for more than 99% of businesses (ANIF & Bancolombia, 2021), this concern is particularly relevant: larger establishments command greater financial resources and better access to external financing, enabling higher absolute ICT expenditure independently of their actual degree of digitalization. A small establishment investing a large share of its asset base in ICT may be more technologically intensive than a large establishment spending a greater absolute amount while devoting a negligible fraction of its resources to digital technologies. Monetary ICT investment therefore conflates technological intensity with firm scale. To address this, three scale-adjusted measures are constructed as robustness explorations: **(i)** ICT equipment investment as a share of total fixed assets, **(ii)** as a share of total investment in fixed assets, and **(iii)** as a share of total sales. The ICT investment-to-sales ratio in particularly interesting because an establishment that might be investing more than its total sales may indicate that it is in an investment spree trying to catch up or even deploying some kind of strategy, The three are estimated under the identical System GMM specification as the main dependent variable. Results are discussed in Section 6.3 (Robustness Checks).

Because those measures are ratios in levels rather than log-transformed values, coefficients on log-transformed regressors carry a semi-elasticity interpretation, meaning that a 1% increase in the regressor is associated with a $\beta/100$ unit change in the intensity ratio.

There is one aspect worth highlighting regarding the lag depth used in the main specification. Specifications using shallower instrument lag depths (lags 2-3 and 3-4) were rejected by both the Arellano-Bond AR(2) test and the Sargan/Hansen overidentification test, indicating that the idiosyncratic error exhibits serial correlation beyond the first-order mechanical correlation

workforce composition, that is, the shares of professional/technical workers and managers, which adjusts more slowly than total headcount or investment decisions. Because an ICT investment shock in a given year is unlikely to alter the skill mix of the workforce within that same annual period, this justifies the treatment of the human capital variables in the model as predetermined rather than endogenous in the GMM specification.

introduced by first-differencing. The final specification uses lags 4-5 as GMM instruments for endogenous regressors and lags 3-4 for predetermined regressors, the shallowest depths at which both diagnostic tests are satisfied. However, the deep lag structure necessary to achieve valid instruments comes at the cost of reduced instrument strength, which contributes to the imprecision of the System GMM estimates.

To assess potential attrition bias from restricting the sample to a balanced panel, we compare the means of key variables –including ICT equipment investment, establishment size, labour productivity, export intensity, and human capital– between establishments that remain in the balanced panel and those present only in the unbalanced panel, testing whether the differences are statistically significant. As a further robustness check, we re-estimate the main System GMM specification on the unbalanced panel for the 2018-2023 period, verifying that the coefficient estimates remain stable and that the diagnostic tests are not materially affected. In addition, to verify that the choice of estimation window is not driving the results we re-estimate the model on longer balanced windows: a full-period panel (2012-2023) and a 2015-2023 panel. The number of establishments retained under each window and the corresponding estimates are reported in the attrition analysis of Section 6.2 (Robustness Checks).

To further analyse the heterogeneity of the sample, we estimate the main specification grouping by establishment size: (a) micro, which are establishments with fewer than 10 employees but with a production value exceeding the annual threshold set by the PPI; (b) small, with between 10 and 50 employees; (c) medium, with between 51 and 200; and (d) large, which are establishments with more than 200 employees.

In addition, a Pearson correlation matrix of the key variables explored in this investigation is presented. A complementary classification of establishments as active or inactive ICT investors, based on the regularity of ICT investment across observed years, is proposed as a direction for future research (see Section 7).

4. Data

This research utilizes establishment-level panel data from the National Administrative Department of Statistics' –DANE EAM for the period 2012-2023. The EAM provides comprehensive information on manufacturing establishments' operations with 10 or more employees or establishments with less than 10 employees and a production value higher than that stipulated annually by the Producer Price Index (PPI), investment patterns, employment composition, and geographic distribution. It includes a specific module on ICT, offering information on establishments' investment in related equipment (DANE, 2024).

The panel covers 2012 onwards for two methodological reasons. First, DANE adopted the International Standard Industrial Classification Revision 4 (ISIC Rev. 4) starting in 2012, ensuring a consistent industry classification throughout the study period; earlier years used ISIC Rev. 3, which is not directly comparable at the 4-digit level without a conversion crosswalk. Second, the export variable (PORCVT) changed definition between 2007 and 2008 (from a percentage of sales exported to an absolute value in Colombian pesos (COP)). This makes pre-2008 export data incompatible with later years without additional transformation. Given the survey-based nature of the data, which follows manufacturing establishments over time, the analysis employs two complementary panel structures.

Table 4.1. Descriptive Statistics: Full Unbalanced Panel (2012-2023)

	count	mean	sd	min	p25	p50	p75	max
Real ICT investment[a]	97,250	33,949.48	323,922.92	0.00	0.00	0.00	9,049.88	44,014,720.00
Log of ICT investment	97,250	4.56	4.80	0.00	0.00	0.00	9.11	17.60
ICT inv/Sales	97,108	0.00	0.06	0.00	0.00	0.00	0.00	10.73
ICT inv/Fixed assets	96,157	0.00	0.03	0.00	0.00	0.00	0.00	3.15
ICT inv/Total inv fixed assets	65,486	0.13	0.25	0.00	0.00	0.02	0.10	1.00
Total employment (size)	97,128	86.73	158.80	1.00	14.00	32.00	88.00	3,619.00
Labor productivity[a]	97,128	108,319.83	700,469.50	-1,930,132.25	24,161.99	43,432.84	80,983.77	91,490,688.00
Exports/sales (intensity)	87,854	0.06	0.17	0.00	0.00	0.00	0.01	1.00
Share of professional and technical workers	97,128	0.10	0.14	0.00	0.00	0.06	0.15	1.00
Share of managerial staff	97,128	0.29	0.20	0.00	0.15	0.25	0.40	1.00

Note. Establishment-level variables in constant 2018 prices, full unbalanced panel (2012-2023). Source: own elaboration based on EAM (DANE).
[a]Monetary values are all in real terms (base year 2018=100) and thousands of COP.

For the descriptive analysis, the full unbalanced panel is used to document trends and patterns of ICT equipment investment across the entire population of manufacturing establishments, preserving the full variation in ICT equipment investment behaviour, including entry and exit dynamics, and ensuring representativeness of the Colombian manufacturing sector as a whole.

Following Gallego et al. (2024), all monetary variables are expressed in constant 2018 Colombian pesos (COP). ICT equipment investment, total fixed assets, and total investment in fixed assets are deflated using DANE's Producer Price Index for capital goods (IPP "Bienes de Capital"); sales and value added (from which labor productivity is derived) are deflated using DANE's Producer Price Index for manufacturing output (IPP "Producción Nacional", Section C). Both indices are annual averages rebased to 2018 = 100, sourced from DANE's official IPP publications.

4.1. Data limitations

The export intensity variable is unavailable for 2014 due to the absence of the exports variable (PORCVT) in that year's EAM microdata for both the firm and establishment levels. This limitation, combined with the resulting gaps in the balanced sub-panel, contributed to the decision to exclude Period 1 (2012–2017) from the GMM estimation entirely: the gaps invalidated the moment conditions underlying the System GMM estimator, prevented computation of the AR(2) serial correlation diagnostic, and produced borderline Sargan/Hansen test results. The Period 2 (2018–2023) specification, which constitutes the main empirical contribution of this thesis, is unaffected: export intensity is available for all six years in that period and is included as a regressor in all specifications.

An alternative source of export data, such as LegisComex, which provides firm-level international trade records for Colombia, was considered but is not feasible for two reasons. First, LegisComex identifies firms by NIT (tax identification number), whereas the EAM anonymizes firms and establishments using an internal identification number (*nordemp* for firms, and *nordest* for establishments); the crosswalk between these two identifier systems is not available under the data access conditions of this study, making any record linkage impossible in practice. Second, even if linkage were achievable, LegisComex provides data at

Table 4.2. Descriptive Statistics: Balanced Sub-Panels

	count	mean	sd	min	p25	p50	p75	max
Panel A: Pre-estimation balanced panel (2012-2017)								
Real ICT investment[a]	43,152	32,794.50	283,122.74	0.00	0.00	912.70	10,257.12	34,418,216.00
Log of ICT investment	43,152	4.93	4.76	0.00	0.00	6.82	9.24	17.35
ICT inv/Sales	43,081	0.00	0.03	0.00	0.00	0.00	0.00	5.76
ICT inv/Fixed assets	42,820	0.01	0.03	0.00	0.00	0.00	0.00	3.15
ICT inv/Total inv fixed assets	31,142	0.13	0.25	0.00	0.00	0.02	0.10	1.00
Total employment (size)	43,116	88.10	160.33	1.00	16.00	34.00	88.00	3,619.00
Labor productivity[a]	43,116	111,493.88	926,372.07	3.23	25,748.29	43,912.21	78,039.20	91,490,688.00
Exports/sales (intensity)	35,894	0.06	0.16	0.00	0.00	0.00	0.01	1.00
Share of professional and technical workers	43,116	0.09	0.13	0.00	0.00	0.06	0.14	1.00
Share of managerial staff	43,116	0.29	0.20	0.00	0.15	0.25	0.40	1.00
Panel B: Estimation balanced panel (2018-2023)								
Real ICT investment[a]	38,466	42,596.55	386,800.15	0.00	0.00	666.92	12,587.95	44,014,720.00
Log of ICT investment	38,466	4.91	4.91	0.00	0.00	6.50	9.44	17.60
ICT inv/Sales	38,429	0.00	0.08	0.00	0.00	0.00	0.00	10.73
ICT inv/Fixed assets	38,118	0.00	0.02	0.00	0.00	0.00	0.00	1.00
ICT inv/Total inv fixed assets	27,109	0.12	0.24	0.00	0.00	0.02	0.09	1.00
Total employment (size)	38,439	102.70	172.20	1.00	18.00	42.00	112.00	2,401.00
Labor productivity[a]	38,439	118,730.86	492,377.45	-347,322.66	27,123.12	48,657.31	94,102.09	42,080,240.00
Exports/sales (intensity)	38,426	0.07	0.17	0.00	0.00	0.00	0.03	1.00
Share of professional and technical workers	38,439	0.11	0.14	0.00	0.00	0.07	0.17	1.00
Share of managerial staff	38,439	0.29	0.20	0.00	0.15	0.25	0.40	1.00

Note. Establishment-level variables in constant 2018 prices, for the balanced sub-panels. Source: own elaboration based on EAM (DANE).
[a]Monetary values are all in real terms (base year 2018=100) and thousands of COP.

the firm level, whereas this study's unit of observation is the establishment –a finer level of disaggregation that trade databases do not reach.

For 132 establishment-year observations, total sales are reported as zero in the EAM microdata, rendering the ICT equipment investment-to-sales ratio undefined. The ICT equipment investment-to-sales ratio variable is set to missing for these observations; the underlying establishment-year records are retained in the dataset and contribute to all specifications that do not use this ratio.

Table 4.3. Pearson Correlation Matrix, Period 2 Balanced Panel (2018-2023)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Log of ICT investment	1.000							
(2) ICT inv/Fixed assets	0.161***	1.000						
(3) ICT inv/Total inv fixed assets	0.235***	0.288***	1.000					
(4) Log of total employment	0.488***	-0.062***	-0.186***	1.000				
(5) Log of labour productivity	0.293***	-0.019***	-0.127***	0.230***	1.000			
(6) Exports/sales (intensity)	0.182***	0.004	-0.035***	0.219***	0.178***	1.000		
(7) Share of professional and technical workers	0.159***	0.011*	-0.011*	0.125***	0.245***	0.113***	1.000	
(8) Share of managerial staff	0.091***	0.090***	0.137***	-0.109***	-0.005	-0.073***	-0.168***	1.000

Note: Pearson correlations (listwise, N = 27,073), estimation sample: Period 2 balanced panel (2018-2023).
* p<0.10, ** p<0.05, *** p<0.01.

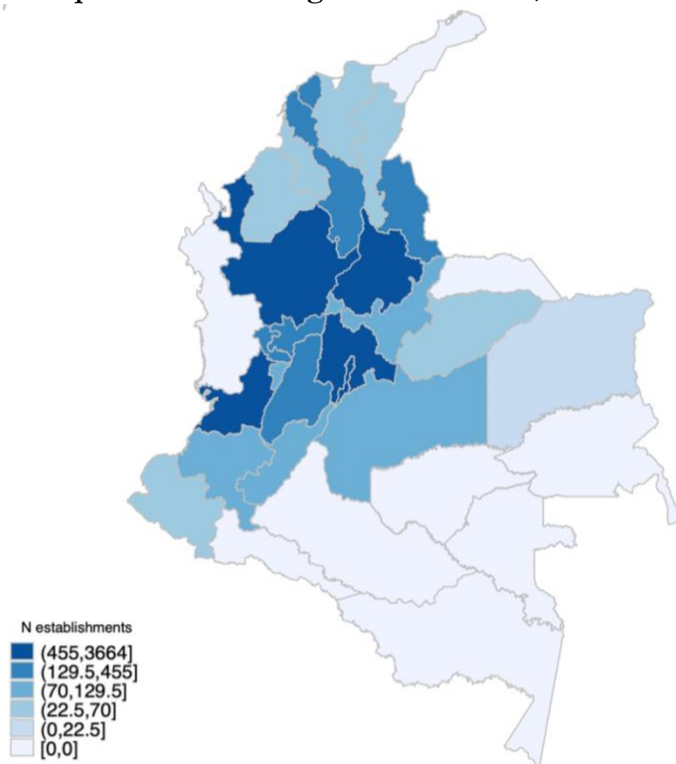
4.2. Descriptive statistics

Real ICT equipment investment exhibits two distinct forms of heterogeneity. Table 4.1 reports descriptive statistics for the full 2012-2023 panel, while Table 4.2. presents descriptive statistics for two balanced sub-panels: Panel A presents the descriptives for the 2012-2017 sub-period and Panel B for the 2018-2023 sub-period (estimation period). First, on the extensive margin,[12] the median value is zero, consistent with the roughly 51% of establishment-year observations reporting no ICT equipment investment in a given year. Second, the distribution of investment amounts is extremely right-skewed: across the full panel, in constant 2018 prices, the standard deviation (COP 324 million) is roughly nine and a half times the mean (COP 34 million), and the maximum value (COP 44.0 billion) is approximately 390 times the 95th percentile (COP 113.1 million; Table 1a).

This pattern indicates that the sample mean may be driven by a small number of very large establishments –relative to total number of establishment-year observations in the sample (97,250)– rather than representing a "typical" investing establishment and motivates both the log transformation $ln(ICT + 1)$ used in the main specification and the size-heterogeneity robustness checks discussed in Section 6.4. The ICT equipment investment-to-Total investment in fixed assets ratio shows a particular decrease in the number of observations by the order of around 32 thousand observations in the full unbalanced panel due to a zeros problem in the denominator which is automatically managed by STATA by setting to missing values that are mathematically undefined.

[12] In this context the extensive margin refers to an establishment's decision whether to invest in ICT, whereas the intensive margin refers to how much an establishment invests, given that it invests at all.

Figure 4.1. Establishment Density by Region
Unique manufacturing establishments, 2012-2023

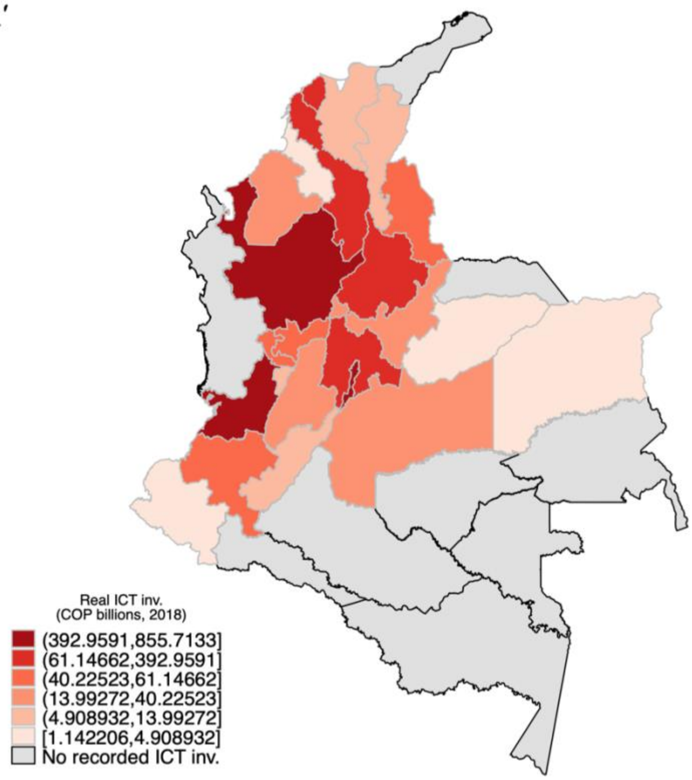


Source: EAM (DANE).
Note: Full unbalanced panel, 2012–2023

Another aspect that stands out is the fact that for the ICT equipment investment-to-sales ratio the maximum value exceeds one (>1), reaching 10.73 in the estimation panel (Table 4.2., Panel B; 13 establishment-year observations). This is economically plausible: an ICT-intensive establishment may invest more in ICT equipment in a given year than its total reported sales, and such observations are retained as informative rather than treated as errors. For the ICT equipment investment-to-fixed assets ratio, values above one arise only in the pre-estimation period, i.e., Panel A (2012-2017; max 3.15), not in the balanced estimation panel (2018-2023), and are likewise retained. It is also possible that the total investment in fixed assets of an establishment could consist entirely of ICT assets.

That may be the case for smaller, ICT-intensive manufacturing establishments. The same applies for establishments in which all its employees are either professional and technical workers or that all are considered managerial staff. A value of 1 for the export-to-sales ratio suggests that there is at least one establishment in which all its sales are exports, making it a complete exporter. The right-skewness emerges in Panels A and B as well, though the balanced sub-panels are more ICT-active with positive median investment values reflecting that continuously observed establishments invest more regularly.

Figure 4.2. ICT equipment investment by Region (Real prices, 2018=100)

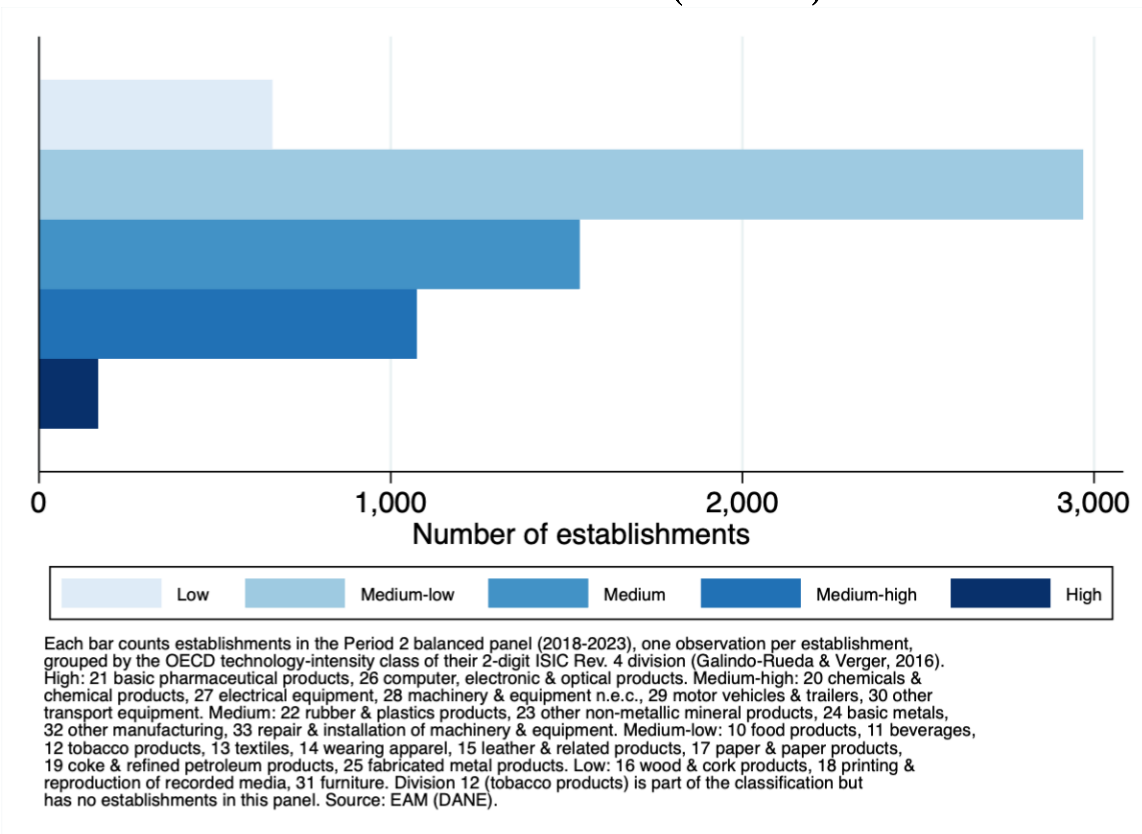


Source: EAM (DANE). Departments without manufacturing establishments in the EAM shown in grey.
Note: Full unbalanced panel, 2012–2023

Table 4.3 presents the Pearson correlation matrix of the key variables for the estimation sample. Interestingly, though most variables show statistically significant correlations between them (ranging from the 10% level to the 1% for most correlations), some exhibit negative correlations. That is the case between both ICT equipment investment as a share of fixed assets and as a share of total investment in fixed assets, and total employment, labour productivity and even exports intensity (log form).

Additionally, most manufacturing establishments in the EAM are located in the Andean region of Colombia, namely, Bogotá D.C. (35.4%), Antioquia (21.18%), Valle del Cauca (12.8%), Cundinamarca (6.49%), and Santander (4.75%), which amass the highest number of establishments with 8,726 –nearly 81% of the total. Those are followed by Tolima, Caldas, Risaralda, Norte de Santander, Bolívar and Atlántico (Figure 4.1; Table 4a). Similarly, the regions –or departments or states– that exhibit the highest ICT equipment investment values are Bogotá D.C., Antioquia and Valle del Cauca, followed by Cundinamarca, Santander, Bolívar and Atlántico (Figure 4.2). This sheds a light not only on the most industrialized regions of Colombia, but also on which of those regions are the heaviest ICT investors of the manufacturing sector.

Figure 4.3. Establishments by OECD Technology Intensity Group
Period 2 Balanced Panel (2018-2023)



Source: own elaboration based on EAM (DANE).

The estimation sample is concentrated in low- and medium-technology manufacturing. Classifying establishments by the OECD taxonomy of technological intensity (Galindo-Rueda & Verger, 2016), which maps the two-digit ISIC Rev. 4 divisions into five R&D-intensity groups, nearly half of the 6,411 establishments in the Period 2 balanced panel (46.3%) operate in medium-low-technology divisions and a further 24.0% in medium-technology divisions. Medium-high-technology divisions account for 16.8% and low-technology divisions for 10.3%, whereas only 2.6% belong to high-technology divisions –pharmaceuticals and computer, electronic and optical products (Figure 4.3). This composition mirrors the structure of Colombian manufacturing, in which technologically sophisticated activities remain a small share of the establishment base, and is consistent with the modest aggregate ICT-investment intensity documented above.

5. Results & Discussion

Table 5.1 presents the main estimation result for the OLS, Fixed Effects and the baseline specifications in columns (1), (2) and (3), respectively. As previously stated, the OLS and the Fixed Effect estimates provide the upper and lower bounds benchmarks for the System GMM α estimate, respectively. The point estimate of 0.216 for the lagged dependent variable in between the α coefficients of the OLS (0.358) and the Fixed Effects (-0.081) estimates indicates that the System GMM estimator is consistent with a well-specified System GMM estimator (Bond, 2002), although the coefficient itself is imprecisely estimated. It must be acknowledged, however, that the lagged dependent variable coefficient isn't significant even at the 10% level. Although the OLS and Fixed Effects estimates have several coefficients that appear to be significant at the 1% level, these are not reliable due to endogeneity concerns that prompted the use of the System GMM in the first place and therefore may be biased.

Table 5.1. Period 2 (2018-2023): Main Estimation Results

	(1) OLS b/se	(2) Fixed Effects b/se	(3) System GMM b/se
Log ICT Inv (t-1)	0.358***	-0.081***	0.216
	(0.007)	(0.007)	(0.184)
Log employment	1.349***	2.129***	1.616***
	(0.027)	(0.083)	(0.400)
Log labor productivity	0.515***	0.465***	0.530
	(0.024)	(0.045)	(0.365)
Export intensity	1.197***	1.075***	-0.655
	(0.135)	(0.279)	(3.409)
% prof./technical workers	1.752***	0.849***	-0.566
	(0.176)	(0.303)	(1.799)
% managerial workers	2.119***	1.472***	1.657
	(0.129)	(0.298)	(1.494)
Year 2019			0.141**
			(0.060)
Year 2020	-0.242***	-0.178***	-0.077
	(0.064)	(0.052)	(0.076)
Year 2021	-0.022	-0.149***	0.083
	(0.058)	(0.057)	(0.085)
Year 2022	0.045	-0.034	0.166**
	(0.058)	(0.058)	(0.074)
Observations	31,996	31,996	31,996
N establishments		6,406	6,406
AR(1)			0.001
AR(2)			0.402
AR(3)			0.719
Sargan			0.181
Diff-in-Sargan			0.192
Underid			0.455

Note: AR(1), AR(2), Sargan, Diff-in-Sargan and Underid all report p-values.
Standard errors reported in parenthesis.
2018 is not reported as it's the base year; 2023 is not included because it's mechanically omitted due to collinearity.

The only coefficient that is significant at the 1% is the one for the size of the establishment measured as employment, with an elasticity of 1.616, meaning that for an increase of 1% in employment (or size) of the establishment, there's an increase of 1.616% in ICT equipment investment in that establishment. As noted in some of the literature reviewed (Aboal and Tacsir, 2018), economies of scale may play a role here, since larger firms can make greater investments in ICT (particularly in hardware) and generate higher demand for these technologies, which allows them to negotiate better terms with ICT suppliers. From the perspective of Resource-Based View (RBV) theory, this result can be explained by the fact that the size of an establishment is in itself a valuable, rare, imperfectly imitable, and non-substitutable resource which, in the context of the Colombian manufacturing sector –where most firms, let alone establishments, are MSMEs– translates into a sustainable competitive advantage, as larger establishments are expected to have more resources and better access to financing, allowing them to invest more money in ICT.

Regarding the importance of size for ICT equipment investment, this finding is consistent with the previous empirical evidence on ICT adoption and appropriation of returns on ICT equipment investment (Aboal & Tacsir, 2018; Gallego et al., 2015; Gallego et al., 2024), which suggests that the size of the firms and establishments is determinant in relation to ICT. Indeed, Gallego et al. (2015) found that, in 2006, larger manufacturing firms in Colombia were more likely to adopt ICT which, alongside human capital in their case, suggests that the resources available to large firms, including greater cash flows and more access to finance (cheaper debt), allow them to invest more heavily in ICT and increasing the probability of adopting these technologies. Thus making size crucial for both ICT adoption and investment. Similarly, Aboal and Tacsir (2018) consistently find that firm size is positively correlated with the investment decision in ICT, with size playing a bigger role for the manufacturing than for the services sector in Uruguay. With respect to firm productivity, Aboal and Tacsir (2018) find that size is positively correlated specifically for manufacturing firms.

These results are also consistent with Cataldo et al. (2020) who looked at the ICT maturity of Chilean MSMEs in 2009 and found that firm size plays a crucial role on the impact of ICTs on firm performance given their ICT maturity stage. Although their findings suggest that ICT assets have a greater impact on micro and small businesses, contrary to what most studies show, these findings come with a key caveat: specifically, the impact is observed in those businesses that are clearly ICT-intensive or technology-driven, regardless of their size.

In other words, as they point out, they observe a greater impact on the performance of micro and small enterprises that are at an intermediate or advanced stage of ICT maturity, while the effect was absent for medium size firms. Thus, one could say that those results show some kind of diminishing returns. Although they introduced sector-specific controls, their results could be influenced by sectoral heterogeneity, meaning that firms in more technology-intensive sectors –regardless of their specific industry– might, by their very nature, be at more advanced stages of ICT maturity.

The lagged dependent variable is imprecisely estimated, consistent with an episodic rather than strongly persistent investment pattern among Colombian manufacturing establishments, though the positive, between-bounds estimate explains the dynamic term retention rather than its restriction to $\alpha = 0$. Given the evidence gathered through this work suggesting episodic ICT equipment investment among Colombian manufacturing establishments, one can conclude that for most establishments ICT equipment investment does not appear to function as a valuable resource providing a sustainable competitive advantage or a dynamic capability that enables establishments to better organise themselves to exploit their available resources, because for that to be the case it would be necessary for the establishments to consistently and continuously update the ICT fixed assets in order to make sure they avoid having obsolete and outdated ICT equipment, which can prevent establishments from getting the most out of those resources. This can be explained by the fact that the Colombian manufacturing sector is mainly comprised of SMEs in low technological-intensity sectors (Figure 4.3) and that the ICT equipment investment measured by the EAM survey focuses exclusively on ICT equipment as fixed assets. An alternative explanation could be that the monetary indicator of investment in ICT equipment does not capture use and adoption, nor returns.

This is reflected in the sample used for the estimation (417 micro; 3,103 small and 2,034 medium-establishments; Table 6.6). The policy implications of these findings are multiple. Intermittent investment in ICT equipment means establishments invest only when previously owned ICT equipment needs to be updated or changed, which reflects the normal replacement cycle of durable equipment. The problem arises when the replacement of obsolete ICT equipment is delayed due to capital constraints. Ideally, investment in ICT equipment should be appropriately planned and periodically done so establishments do not end up with old, obsolete and outdated equipment that would prevent it from becoming a valuable resource in the RBV sense.

Table 5.2. Variance Decomposition: Overall, Between and Within Variation, Period 2 Balanced Panel (2018-2023)

	Mean	SD overall	SD between	SD within	Within share (%)
Real ICT investment[a]	42,596.55	386,800.15	192,059.61	335,756.24	75.3
Log of ICT investment	4.91	4.91	3.95	2.91	35.2
ICT inv/Sales	0.00	0.08	0.03	0.07	82.6
ICT inv/Fixed assets	0.00	0.02	0.01	0.02	62.9
ICT inv/Total inv fixed assets	0.12	0.24	0.20	0.18	45.9
Total employment (size)	102.70	172.20	166.40	44.28	6.6
Labour productivity[a]	118,730.86	492,377.45	436,690.93	227,507.39	21.3
Exports/sales (intensity)	0.07	0.17	0.15	0.07	19.3
Share of professional and technical workers	0.11	0.14	0.12	0.07	25.6
Share of managerial staff	0.29	0.20	0.18	0.07	13.7

Note: Within share = SD² within / (SD² between + SD² within), in percent. Sample: Period 2 balanced panel (2018-2023), 6,411 establishments × 6 years = 38,466 establishment-year observations.
[a]In thousands of constant 2018 COP.

Thus, policymakers could reintroduce tax incentives related to the acquisition of technology and capital goods, similar to those created in Laws 1607 of 2012 and 1819 of 2016 (See Table 1.1.). In addition, access to leasing could be expanded since it is well suited to ICT equipment because it transfers obsolescence risk to the lessor and converts lumpy capital outlays into smoother payment streams. This could be achieved through programs aimed at raising awareness of leasing as an alternative among micro, small and medium size establishments (see Figure 2a), and through public guarantees that would let leasing companies serve higher-risk small establishments. Finally, policymakers could introduce tax incentives to make leasing ICT equipment a more attractive alternative for establishments.

These results diverge from earlier evidence linking human capital to ICT adoption in Latin American manufacturing (Gallego et al., 2015; Aboal & Tacsir, 2018), although the comparison is not exact since those studies differ in several aspects, and more importantly model ICT adoption or stock rather than the flow of investment examined here. To assess whether the null human-capital result masks size-specific heterogeneity, the model was re-estimated separately for micro, small, medium, and large establishments using time-invariant size tiers. The results are presented in Section 6.4 (Robustness Checks).

The pattern of insignificance across labour productivity, export intensity, and workforce composition variables reflects a common identification constraint: as Table 5.2 shows, within-establishment variation is limited for all these regressors, ranging from 6.6% for employment to 25.6% for professional and technical workers, meaning the System GMM difference equation has little variation to exploit. This does not necessarily imply these characteristics are unrelated to ICT equipment investment; rather it implies that establishments with higher labour productivity, greater export orientation, and richer human capital tend to maintain those characteristics stably over time, so the within-estimator cannot separate their effect from the establishment fixed effect.

The year coefficients reveal meaningful temporal variation in ICT equipment investment beyond what is explained by establishment characteristics. The coefficients for 2019 and 2022 are statistically significant at the 5% level, indicating that average ICT equipment investment in those years was significantly higher than in the base year (2018), conditional on establishment fixed effects and time-varying regressors. The coefficients for 2020 and 2021 – the years of the COVID-19 pandemic– are not statistically significant, suggesting that the pandemic's immediate and mediate disruption did not produce a detectable aggregate change in ICT equipment investment relative to 2018. The significant and positive coefficient for 2022 is consistent with a post-pandemic digitalization response, as establishments seem to have accelerated ICT equipment investment during the recovery period in response to pandemic-induced demand for remote work, digital channels, and process automation, with the uptick in aggregate ICT equipment investment visible from 2021 onward (Figure 1a) suggesting the recovery began before the 2022 conditional peak identified by the GMM specification. However, because all monetary values are expressed in constant 2018 prices, these year coefficients capture real changes in ICT equipment investment net of price effects, notwithstanding the substantial inflation Colombia experienced during 2021-2022, when annual consumer price inflation peaked above 13% in early 2023 (DANE, 2023). The significant and positive coefficient for 2022 therefore reflects a genuine increase in real ICT equipment spending during the post-pandemic recovery rather than a price-level artefact.

All three diagnostic tests support the System GMM specification for Period 2: the Arellano-Bond AR(1) test rejects the null of no autocorrelation as expected ($p = 0.001$), AR(2) does not reject ($p = 0.402$), and the Sargan/Hansen overidentification test does not reject ($p = 0.181$), meaning the instruments used in this specification are valid. The Difference-in-Sargan/Hansen test for the joint validity of level-equation instruments yields $p = 0.192$, supporting the mean stationarity assumption. Though the diagnostic tests are satisfied, the deep lag structure necessary to achieve valid instruments comes at the cost of reduced instrument strength, which contributes to the imprecision of the System GMM estimates. Consistent with this limited strength, the joint Kleibergen-Paap underidentification test fails to reject the null of underidentification ($p = 0.455$); the per-regressor underidentification statistics, however, reject the null for every endogenous regressor individually ($p < 0.01$, the weakest being export intensity at $p = 0.0005$), so each coefficient is separately identified. The imprecision of the System GMM estimates should therefore be read as a symptom of weak instrument strength rather than of a coefficient being unidentified, and the results are interpreted with corresponding caution.

A potential concern regarding the monetary measurement of ICT equipment investment is discussed in Section 6.3 (Robustness Checks), where scale-adjusted intensity measures are constructed and evaluated.

These results suggest that, for most establishments in the Colombian manufacturing sector, investment in ICT equipment does not yet constitute a strategic resource in the sense of Barney (1991), nor does it underpin the development of dynamic capabilities in the sense of Teece et al. (1997). This reflects the sector's structural characteristics: a manufacturing fabric composed mainly of micro, small, and medium establishments operating in low and medium-low R&D intensity sectors, which invest in ICT fixed assets only episodically. Because ICT equipment depreciates and becomes obsolete, inttermitent investment leaves establishments without the consistently updated technological base that sustained competitive advantage requires, preventing ICT from functioning as a valuable, rare, and imperfectly imitable resource, or from enabling the continuous reconfiguration of resources that dynamic capabilities entail.

6. Robustness checks

To test the sensitivity of the results, we estimated several other specifications: from Difference GMM to the main specification without the 2023 dummy, different dependent variables, partitioned samples by size and so on. All are reported and discussed in this section. Alternative lag structures were tested and rejected (see Table 5a in the Appendix). Specifications using lag depths starting at lag 2 or lag 3 produced Arellano-Bond AR(2) rejections ($p < 0.01$) and Sargan/Hansen overidentification rejections ($p < 0.01$), indicating instrument invalidity. Relaxing the collapse restriction in the preferred specification marginally improved coefficient precision on labor productivity but caused the Sargan/Hansen test p-value to fall to 0.030 under the three-step weighting matrix, suggesting instrument proliferation (Roodman, 2009). As seen in the previous section, the final specification (lag 4-5 for endogenous, lag 3-4 for predetermined, with collapsed instruments) passes all standard diagnostics: AR(1) $p = 0.001$, AR(2) $p = 0.402$, Sargan/Hansen $p = 0.181$. Since shallower lag structures did not pass any of these tests, those results are not reported here.

6.1. Difference GMM and no-2023 dummy

Table 6.1 presents results for the Difference GMM in column (1), and the System GMM specification without the 2023-time dummy to test the sensitivity of the results in column (2). First, as column (2) of Table 6.1 shows, the coefficients and standard errors are identical to those of the main System GMM specification presented in Table 5.1, column (3). This suggests that the results are robust to the treatment of the collinear endpoint dummy, which is mechanically omitted by the model. The Difference GMM specification *a priori* tells an encouraging story, since it does not reject the null of valid instruments for the Sargan/Hansen test of overidentifying restrictions (0.205), and borderline rejects the null of weak identification of the Kleibergen-Paap test of underidentification (0.048).

However, the story becomes grim when one closely investigates the coefficients, standard errors and the AR(1) test of first-order serial correlation, given that AR(1) is expected in for the Difference GMM estimator by design. As can be seen, none of the coefficients is statistically meaningful, even at the 10% level. The standard errors are big, indicating highly imprecise and potentially biased estimates, generally downwardly biased.

Table 6.1. Robustness Checks: Diff GMM & Sys GMM (No 2023 dummy)

	(1) Difference GMM	(2) Sys-GMM (no 2023 dummy)
	b/se	b/se
Log ICT Inv (t-1)	-0.206	0.216
	(0.221)	(0.184)
Log employment	0.912	1.616***
	(2.041)	(0.400)
Log labour productivity	0.895	0.530
	(0.813)	(0.365)
Export intensity	-0.148	-0.655
	(6.410)	(3.409)
% prof./technical workers	-2.293	-0.566
	(2.771)	(1.799)
% managerial workers	6.130	1.657
	(4.096)	(1.494)
Year 2019	0.165	
	(0.102)	
Year 2020	-0.060	
	(0.160)	
Year 2021	-0.067	
	(0.098)	
Year 2022	0.122	
	(0.075)	
Year 2019		0.141**
		(0.060)
Year 2020		-0.077
		(0.076)
Year 2021		0.083
		(0.085)
Year 2022		0.166**
		(0.074)
Observations	31,996	31,996
N establishments	6,406	6,406
AR(1)	0.204	0.001
AR(2)	0.199	0.402
Sargan	0.214	0.181
Diff-in-Sargan		0.192
Underid	0.036	0.455

Note: Note: Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01. AR(1), AR(2), AR(3), Sargan, Diff-in-Sargan and Underid all report p-values.

Concretely, the lagged dependent variable and the size (log employment) coefficients are smaller than that of the System GMM estimation, and even negative for the lagged dependent variable, indication of the downward bias expected for the first-differences GMM estimator with finite sample bias (Blundell & Bond, 1998; Blundell & Bond 2000; Blundell, Bond & Windmeijer, 2000; Bond, 2002). Finally, an AR(1) p = 0.204 means it fails to reject the null of no autocorrelation of order 1, which as stated, is expected due its mechanical introduction through first-differencing to remove the fixed effects. These results support the methodological choice of the System GMM estimator, which recover efficiency through the levels equation.

6.2. Attrition analysis

The cost of the balanced-panel restriction is moderate. Of the 10,824 establishments in the unbalanced panel, 7,192 (66%) are observed in all six years of 2012-2017 and 6,411 (59%) in all six years of 2018-2023, while 6,052 (56%) survive the nine years 2015-2023 and 5,642 (52%) the full twelve years 2012-2023. Attrition is therefore gradual rather than severe: roughly half of all establishments persist across the entire period, and each six-year sub-panel retains several hundred more establishments than a full-period balanced panel would.

Table 6.2. Period 2 (2018-2023): Balanced vs Unbalanced Panel

	(1) Balanced (Main) b/se	(2) Unbalanced b/se
Log ICT Inv (t-1)	0.216	0.198
	(0.184)	(0.150)
Log employment	1.616***	1.687***
	(0.400)	(0.292)
Log labour productivity	0.530	0.648**
	(0.365)	(0.311)
Export intensity	-0.655	1.084
	(3.409)	(3.208)
% prof./technical workers	-0.566	-0.475
	(1.799)	(1.723)
% managerial workers	1.657	1.695
	(1.494)	(1.437)
Year 2019	0.141**	0.108*
	(0.060)	(0.058)
Year 2020	-0.077	-0.049
	(0.076)	(0.071)
Year 2021	0.083	0.073
	(0.085)	(0.071)
Year 2022	0.166**	0.126*
	(0.074)	(0.066)
Observations	31,996	35,158
N establishments	6,406	7,746
AR(1)	0.001	0.000
AR(2)	0.402	0.385
AR(3)	0.719	0.712
Sargan	0.181	0.031
Diff-in-Sargan	0.192	0.031
Underid	0.455	0.002

Note: Note: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. AR(1), AR(2), AR(3), Sargan, Diff-in-Sargan and Underid all report p-values.

Table 6.2 compares the results of the System GMM specification for a balanced (main estimation) and unbalanced 2018-2023 panel. Column (2) presents the result for the unbalanced panel. Crucially, the unbalanced panel retains 3,162 more observations and 1,340 more establishments for the same period (2018-2023). The size and labour productivity coefficients the unbalanced estimates are both positive and statistically significant at 1% and 5% levels, respectively. Nonetheless, that specification fails the Sargan/Hansen ($p = 0.031$) and the Difference-in-Sargan/Hansen ($p = 0.031$), indicating that the overidentifying restrictions are rejected and the instruments cannot be considered valid for this specification. STATA reports that the unbalanced panel has gaps, which could contribute to this issue.

Table 6.3. System GMM on Alternative Balanced Windows

	(1) T=9 (2015-2023) b/se	(2) T=12 (2012-2023) b/se
Log ICT Inv (t-1)	0.568***	0.524***
	(0.112)	(0.094)
Log employment	0.898***	0.984***
	(0.312)	(0.268)
Log labour productivity	0.196	0.549***
	(0.256)	(0.188)
Export intensity	-4.904*	
	(2.758)	
% prof./technical workers	0.747	0.243
	(1.264)	(0.878)
% managerial workers	1.076	1.169
	(1.118)	(0.840)
Year 2013		0.540***
		(0.093)
Year 2014		0.384***
		(0.092)
Year 2015		0.311***
		(0.079)
Year 2016	0.248***	0.308***
	(0.080)	(0.073)
Year 2017	0.029	0.044
	(0.075)	(0.072)
Year 2018	0.108*	0.126*
	(0.065)	(0.065)
Year 2019	0.163**	0.180***
	(0.065)	(0.066)
Year 2020	-0.171**	-0.117*
	(0.072)	(0.069)
Year 2021	0.195***	0.166**
	(0.073)	(0.071)
Year 2022	0.238***	0.255***
	(0.076)	(0.076)
Observations	48,316	62,013
N establishments	6,050	5,642
AR(1)	0.000	0.000
AR(2)	0.000	0.000
AR(3)	0.655	0.149
Sargan	0.133	0.009
Diff-in-Sargan	0.024	0.052
Underid	1.000	0.000

Note: Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.
Main 2018-2023 specification re-estimated unchanged on longer windows; only the window differs (T=12 drops export intensity, unavailable in 2014).
Diff-in-Sargan = difference-in-Sargan/Hansen test of the System GMM (lagged-difference) level instruments, from a restricted model dropping the gmm(., model(level)) blocks (year IVs retained for identification).

The 2018-2023 estimation window is itself tested by re-estimating the model on the two longer balanced windows whose retention was reported above. Because export intensity is unavailable in 2014, the full-period (2012-2023) specification omits that regressor; both longer windows use the same lag structure (4 5) as the main specification. Table 6.3 reports the results of each window. Although the lagged dependent variable is statistically significant in both longer windows, these specifications are invalid: each rejects both the AR(2) test and the Sargan/Hansen overidentification test ($p < 0.001$), whereas the main 2018-2023 specification passes both (AR(2) $p = 0.402$, Sargan/Hansen $p = 0.181$). Their apparent precision is an artifact of windows that straddle the 2017/2018 break between the two sub-periods, which induces second-order serial correlation.

The longer window is additionally underidentified, as confirmed by the Kleibergen-Paap test returning $p = 1.000$ –meaning the instruments have no explanatory power for the endogenous regressors in that specification. For both windows, the standard Difference-in-Sargan/Hansen statistic is not computable due to negative degrees of freedom arising from the deep lag structure; the restricted-model approximation documented in the table note is used instead. The sub-period division is therefore driven by the data rather than chosen to maximize sample size.

6.3. Scale-adjusted ICT equipment investment measures

Column (1) of Table 6.4 presents results for the baseline System GMM specification using ICT equipment investment in monetary units, $ln(ICT\ inv. + 1)$, as the dependent variable. Columns (2), (3) and (4) present results for specifications using scale-adjusted measures of ICT equipment investment intensity, namely, ICT equipment investment as a share of total fixed assets, as a share of total investment in fixed assets, and as a share of total sales, respectively. Whereas the coefficients in column (1) are elasticities due to the log-transformed dependent variable, coefficients in columns (2)-(4) are semi-elasticities, since the dependent variables are in levels: a 1% increase in a log-transformed regressor is associated with a $\beta/100$ unit change in the intensity ratio. As can be seen, none of the lagged dependent variable coefficients are statistically significant in any of the specifications. None of the lagged dependent variable coefficients are statistically significant in any of the specifications.

A complementary diagnostic[13] reveals markedly different patterns across the three scale-adjusted measures (reported in full in Table 3a in the Appendix). For investment in ICT equipment as a share of total fixed assets, 97.1% of establishments retain a complete six-year series, with only 2.6% exhibiting internal gaps and 0.3% entirely missing; the corresponding figures for ICT equipment investment as a share of total sales are similarly favourable (99.8% complete, 0.2% gapped, 0.05% fully missing). For these two measures, the zero-denominator treatment has a negligible effect on the panel structure underlying columns (2) and (4) of Table 6.4.

The picture is markedly different for ICT equipment investment as a share of total investment in fixed assets. Only 44.9% of establishments retain a complete six-year series; 46.5% exhibit internal gaps and 8.6% are entirely missing, reflecting the prevalence of establishment-years in

[13] Examining the completeness of each intensity ratio's panel structure within the Period 2 balanced sub-panel (6,411 establishments × 6 years).

which total investment in fixed assets is reported as zero. This severe discontinuity compounds the weak joint identification already noted for column (3) (Underid p = 0.066): the lag-based instrument construction underlying System GMM is not well suited to panels with this degree of internal gaps. Accordingly, the coefficients reported in column (3), including the nominally significant estimates on export intensity and the share of managerial workers, are reported for completeness but should not be interpreted as reliable findings.

Table 6.4. Period 2 (2018-2023):
Baseline System GMM vs. Scale-adjusted ICT Indicators

	(1) ln(ICT inv.) b/se	(2) ICT/Fixed Assets b/se	(3) ICT/Total Inv. b/se	(4) ICT/Total Sales b/se
Log ICT Inv (t-1)	0.216			
	(0.184)			
ICT/Fixed Assets (t-1)		-0.330		
		(0.207)		
ICT/Total Inv (t-1)			-0.075	
			(0.187)	
ICT/Total Sales (t-1)				-0.001
				(0.164)
Log employment	1.616***	0.001	-0.053	0.000
	(0.400)	(0.001)	(0.037)	(0.002)
Log labor productivity	0.530	0.001	-0.017	-0.002
	(0.365)	(0.002)	(0.028)	(0.003)
Export intensity	-0.655	0.014	0.624**	0.009
	(3.409)	(0.019)	(0.300)	(0.059)
% prof./technical workers	-0.566	0.002	-0.035	0.016
	(1.799)	(0.007)	(0.201)	(0.032)
% managerial workers	1.657	0.007	0.312*	0.009
	(1.494)	(0.009)	(0.167)	(0.017)
Year 2019	0.141**	0.000	-0.012*	0.000
	(0.060)	(0.000)	(0.007)	(0.000)
Year 2020	-0.077	-0.001*	-0.002	0.001
	(0.076)	(0.000)	(0.008)	(0.001)
Year 2021	0.083	-0.000	0.005	0.002
	(0.085)	(0.000)	(0.005)	(0.001)
Year 2022	0.166**	0.000	0.001	0.001
	(0.074)	(0.000)	(0.004)	(0.000)
Observations	31,996	31,554	19,590	31,987
N establishments	6,406	6,385	5,104	6,405
AR(1)	0.001	0.324	0.023	0.092
AR(2)	0.402	0.183	0.472	0.993
AR(3)	0.719	0.237	0.743	0.671
Sargan	0.181	0.374	0.374	0.387
Diff-in-Sargan	0.192	0.599	0.333	0.363
Underid	0.455	0.000	0.066	0.486

Note: Note: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. AR(1), AR(2), AR(3), Sargan, Diff-in-Sargan and Underid all report p-values.

The mass point at zero in ICT equipment investment strips out within-establishment variation that the GMM moment conditions require, and the gappiness documented above compounds this for column (3) specifically. As a consequence, the scale-adjusted specifications remain robustness explorations rather than preferred estimates. Notably, the $ln(ICT + 1)$ transformation used in the main specification retains zero observations (they enter as $ln(1) = 0$), but does not fully resolve the underlying heterogeneity: the estimated coefficients reflect a mixture of the extensive margin (the decision whether to invest in ICT at all) and the intensive margin (how much to invest conditional on positive investment). Disentangling these two margins would require a two-part or hurdle model framework and is left for future research.

Table 6.5. Zero vs. Positive ICT equipment investment
Period 2 Balanced Panel (2018-2023)

ICT equipment investment	N	Percent (%)
Zero (real ICT investment = 0)	18,507	48.11%
Positive (real ICT investment > 0)	19,959	51.89%
Total	38,466	100.00%

Note: Establishment-year observations, Period 2 balanced panel (2018-2023). Real ICT equipment investment in constant 2018 COP.

6.4. Heterogeneity analysis –Size

Table 6.6 presents the results of the main specification estimated on four previously constructed size categories using the number of employees in each establishment. The workforce-composition variables remain insignificant across the validly identified tiers, so the pooled result does not appear to conceal a human-capital effect operating within particular size classes. More fundamentally, identification weakens substantially once the sample is partitioned: the Kleibergen-Paap underidentification test fails to reject at conventional levels in every tier (the large-establishment subsample being closest, $p = 0.082$), and the micro subsample additionally violates the second-order serial-correlation and overidentification restrictions. The size-stratified estimates are therefore indicative rather than conclusive and are best read as confirming that the pooled relationships are not driven by any single size class rather than as identifying distinct size-specific dynamics.

Table 6.6. Period 2 (2018-2023): Heterogeneity Analysis by Size

	(1) Micro (1-9) b/se	(2) Small (10-50) b/se	(3) Medium (51-200) b/se	(4) Large (200+) b/se
Log ICT Inv (t-1)	-0.473*	-0.103	0.096	0.230
	(0.242)	(0.246)	(0.239)	(0.265)
Log employment	2.371***	2.066***	1.570**	1.869**
	(0.609)	(0.525)	(0.610)	(0.890)
Log labor productivity	0.712*	1.127**	0.651	2.139
	(0.405)	(0.485)	(0.487)	(1.445)
Export intensity	-0.046	0.938	-6.156	2.216
	(10.101)	(4.262)	(5.065)	(8.815)
% prof./technical workers	6.063**	-3.375	8.481	-2.679
	(2.996)	(2.684)	(5.770)	(5.215)
% managerial workers	6.901*	0.518	6.010*	6.286
	(3.944)	(2.009)	(3.231)	(4.590)
Year 2019	-0.112	-0.042	0.311**	0.286
	(0.263)	(0.105)	(0.130)	(0.304)
Year 2020	-0.058	-0.046	0.007	0.021
	(0.199)	(0.106)	(0.138)	(0.263)
Year 2021	-0.003	-0.082	0.118	-0.021
	(0.228)	(0.120)	(0.128)	(0.185)
Year 2022	0.159	0.036	0.251**	0.070
	(0.168)	(0.089)	(0.121)	(0.169)
Observations	2,078	15,501	10,165	4,252
N establishments	417	3,103	2,034	852
AR(1)	0.500	0.135	0.023	0.022
AR(2)	0.041	0.446	0.764	0.693
AR(3)	0.694	0.665	0.310	0.471
Sargan	0.033	0.203	0.383	0.270
Diff-in-Sargan	0.064	0.390	0.401	0.318
Underid	0.358	0.316	0.146	0.082

Note: Note: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. AR(1), AR(2), AR(3), Sargan, Diff-in-Sargan and Underid all report p-values.

7. Conclusions

Using a System GMM approach, this research estimates the dynamic associations between establishment characteristics and investment ICT equipment for Colombian manufacturing establishments. While ICT equipment investment appeared intermittent rather than strongly persistent over the 2018–2023 sub-period, the dynamic specification is retained because imposing $\alpha = 0$, that is, assuming past investment has no bearing on current investment, is not supported by the cross-estimator evidence.

Establishment size emerges as the only statistically significant determinant of ICT equipment investment, with an elasticity of 1.616, suggesting that a 1% increase in employment is associated with a more than proportional increase in ICT equipment investment. This is consistent with the Resource-based View (RBV): larger establishments command greater financial slack, economies of scale, and bargaining power with ICT suppliers, enabling them to invest more intensively in ICT equipment. Labour productivity, export intensity, and workforce composition are not statistically significant at conventional levels. This does not imply these characteristics are unrelated to ICT equipment investment; rather, as the variance decomposition shows, within-establishment variation in these variables is limited over the estimation period. The year dummies reveal that 2022 stands out as a year of above-average ICT equipment investment relative to the 2018 baseline, consistent with a deferred ICT equipment replacement or acquisition response following the COVID-19 pandemic, as establishments that survived executed investments previously postponed due to liquidity constraints (See Figure 1a). Because the EAM measures investment specifically in ICT fixed assets –computing and communications equipment, which depreciates and becomes obsolete– the intermittent pattern observed implies that many establishments operate with ageing technological infrastructure between investment cycles.

These findings carry important policy implications. The strong and highly elastic association between size and ICT equipment investment, combined with the episodic nature of that investment across the sample, suggests that for most Colombian manufacturing establishments (predominantly micro, small, and medium establishments operating in low and medium-low R&D intensity sectors) ICT does not yet function as a valuable resource or dynamic capability in the RBV and Dynamic Capabilities sense. Because ICT equipment depreciates and becomes obsolete, sustained competitive advantage requires periodic replacement and updating, not one-off acquisition delayed by capital constraints. Policymakers should therefore focus not only on increasing absolute ICT equipment investment but on enabling establishments to maintain a consistently updated technological base. Reintroducing tax incentives related to the acquisition of technology and capital goods, similar to those created in Laws 1607 of 2012 and 1819 of 2016, would reduce the cost of periodic equipment renewal. In addition, expanding MSME access to ICT equipment leasing, which transfers obsolescence risk to the lessor and converts lumpy capital outlays into smoother payment streams, through awareness programs and public guarantees that allow leasing companies to serve higher-risk small establishments, would directly address the episodic investment pattern. More broadly, because establishment size is the strongest determinant of ICT equipment investment, policies that remove unnecessary frictions to MSME growth would indirectly support their capacity to invest in and maintain ICT equipment.

Several avenues for future research emerge from this work. First, as noted in Section 6.3, the dependent variable conflates the extensive margin (whether an establishment invests in ICT equipment at all) and the intensive margin (how much it invests conditional on positive investment). Disentangling these two margins through a two-part or hurdle model framework would clarify whether the determinants of the decision to invest differ from those governing investment magnitude. Second, the classification of establishments as active or inactive ICT investors, defined but not estimated in this thesis, warrants fuller development: a dedicated study modelling the determinants of ICT equipment investment participation, rather than intensity alone, could illuminate the barriers that keep a substantial share of establishments out of ICT equipment investment entirely. Finally, the limited within-establishment variation in labour productivity, export intensity, and human capital composition points to the need for longer panels or higher-frequency data that would generate sufficient variation to identify these effects within establishments.

References

Aboal, D., & Tacsir, E. (2018). Innovation and productivity in services and manufacturing: The role of ICT. *Industrial and Corporate Change*, *27*(2), 221–241.

https://doi.org/10.1093/icc/dtx030
Alderete, M. V., & Gutiérrez, L. H. (2014). Drivers of information and communication technologies adoption in Colombian services firms. *International Journal of Business Information Systems*, *17*(4), 373. https://doi.org/10.1504/IJBIS.2014.065553
ANIF, & Bancolombia. (2021). *Comentario Económico del Día: Retos y oportunidades de las Pymes*. https://www.anif.com.co/comentarios-economicos-del-dia/retos-y-oportunidades-de-las-pymes/
Arellano, M., & Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies*, *58*(2), 277. https://doi.org/10.2307/2297968
Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29–51. https://doi.org/10.1016/0304-4076(94)01642-D
Barney, J. B. (1986). Organizational Culture: Can It Be a Source of Sustained Competitive Advantage? *The Academy of Management Review*, *11*(3), 656–665. https://doi.org/10.2307/258317
Barney, J. B. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108
Bellemare, M. F., & Wichman, C. J. (2020). Elasticities and the Inverse Hyperbolic Sine Transformation. *Oxford Bulletin of Economics and Statistics*, *82*(1), 50–61. https://doi.org/10.1111/obes.12325
Bianchini, M., & Lasheras Sancho, M. (2025). *SME digitalisation for competitiveness* (No. 68; 68th ed., OECD SME and Entrepreneurship Papers). https://doi.org/10.1787/197e3077-en
Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8
Blundell, R., Bond, S., & Windmeijer, F. (2000). *Estimation in dynamic panel data models: improving on the performance of the standard GMM estimator* (WP 00/12; Working Paper Series). https://doi.org/10.1920/wp.ifs.2000.0012
Blundell, R., & Bond, S. (2000). GMM Estimation with persistent panel data: an application to production functions. *Econometric Reviews*, *19*(3), 321–340. https://doi.org/10.1080/07474930008800475
Bond, S. R. (2002). Dynamic panel data models: a guide to micro data methods and practice. *Portuguese Economic Journal*, *1*, 141–162.
Castellani, F., Lotti, G., & Obando, N. (2020). Fixed or open-ended? Labor contract and productivity in the Colombian manufacturing sector. *Journal of Applied Economics*, *23*(1), 199–223. https://doi.org/10.1080/15140326.2020.1729582
Cataldo, A., Pino, G., & McQueen, R. J. (2020). Size matters: the impact of combinations of ICT assets on the performance of Chilean micro, small and medium enterprises. Information Technology for Development, 26(2), 292–315. https://doi.org/10.1080/02681102.2019.1684870
Dejardin, M., Raposo, M. L., Ferreira, J. J., Fernandes, C. I., Veiga, P. M., & Farinha, L. (2023). The impact of dynamic capabilities on SME performance during COVID-19. *Review of Managerial Science*, *17*(5), 1703–1729. https://doi.org/10.1007/s11846-022-00569-x
Departamento Administrativo Nacional de Estadística –DANE. (2026). *Gran Encuesta Integrada de Hogares –GEIH, Mercado Laboral*. DANE. Retrieved March 26, 2026, from https://www.dane.gov.co/index.php/estadisticas-por-tema/mercado-laboral/empleo-y-desempleo and https://www.dane.gov.co/files/operaciones/GEIH/pres-GEIH-

ene2026.pdf
Departamento Administrativo Nacional de Estadística –DANE. (2024). *Metodología General Encuesta Anual Manufacturera –EAM*.
Departamento Administrativo Nacional de Estadística –DANE. (2023). *Índice de Precios al Consumidor –IPC*. DANE. https://www.dane.gov.co/index.php/estadisticas-por-tema/precios-y-costos/indice-de-precios-al-consumidor-ipc
Departamento Nacional de Planeación (DNP). (2025, August 18). *¿Qué es el CONPES?* Departamento Nacional de Planeación. https://www.dnp.gov.co/atencion-al-ciudadano/Paginas/que-es-el-conpes.aspx
Dhrymes, P. (2017). *Introductory Econometrics*. Springer International Publishing. https://doi.org/10.1007/978-3-319-65916-9
Díaz-Arancibia, J., Hochstetter-Diez, J., Bustamante-Mora, A., Sepúlveda-Cuevas, S., Albayay, I., & Arango-López, J. (2024). Navigating Digital Transformation and Technology Adoption: A Literature Review from Small and Medium-Sized Enterprises in Developing Countries. Sustainability, 16(14), 5946. https://doi.org/10.3390/su16145946
Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic Capabilities: What Are They? *Strategic Management Journal*, *21*(10), 1105–1121. http://www.jstor.com/stable/3094429
Eslava, M., Haltiwanger, J., Kugler, A., & Kugler, M. (2014). *The Effects of Regulations and Business Cycles on Temporary Contracts, the Organization of Firms and Productivity* (No. 154; Documentos de Trabajo CEDLAS). www.cedlas.econo.unlp.edu.ar
Galindo-Rueda, F., & Verger, F. (2016). *OECD taxonomy of economic activities based on R&D intensity*. OECD Science, Technology and Industry Working Papers, No. 2016/04. OECD Publishing. https://doi.org/10.1787/5jlv73sqqp8r-en
Gallego, J. M., Gutierrez, L. H., & Lee, S. H. (2015). A firm-level analysis of ICT adoption in an emerging economy: evidence from the Colombian manufacturing industries. *Industrial and Corporate Change*, *24*(1), 191–221. https://doi.org/10.1093/icc/dtu009
Gallego, J. M., & Gutiérrez, L. H. (2015). ICTs in Latin American and the Caribbean Firms: Stylized Facts, Programs and Policies: Knowledge Sharing Forum on Development Experiences: Comparative Experiences of Korea and Latin America and the Ca (IDB-DP-394; Discussion Paper). https://doi.org/10.18235/0007003
Gallego, J. M., Nieves, A., Vargas, F., Díaz, L. M., & Saboin, J. L. (2024). Heterogeneous Returns to ICT Capital: Insights from Colombian Manufacturing Firms (IDB-TN-0378; Technical Note). https://doi.org/10.18235/0013386
Ghaly, M., Anh Dang, V., & Stathopoulos, K. (2017). Cash Holdings and Labor Heterogeneity: The Role of Skilled Labor. *The Review of Financial Studies*, *30*(10), 3636–3668. https://doi.org/10.1093/rfs/hhx045
Griffin, N. N. (2015). *Determinants of Firm Profitability in Colombia's Manufacturing Sector: Exchange Rate or Structural?* (WP/15/97; IMF Working Papers).
Guzman, G. M., Torres, G. C. L., del Carmen Martinez Serna, M., & Garcia Pérez de Lema, D. (2016). Innovation, Information Technology and Performance: An Examination of the Iberoamerican SMEs Context. In D. Bögenhold, J. Bonnet, M. Dejardin, & D. Garcia Pérez de Lema (Eds.), *Contemporary Entrepreneurship* (pp. 111–123). Springer International Publishing. https://doi.org/10.1007/978-3-319-28134-6_7
Hamermesh, D. S., & Pfann, G. A. (1996). Adjustment Costs in Factor Demand. *Journal of Economic Literature*, *34*(3), 1264–1292. https://www.jstor.org/stable/2729502
Heckman, J., & Pagés, C. (2000). *The Cost of Job Security Regulation: Evidence from Latin American Labor Markets* (No. 430; Inter-American Bank Research Dept. Working Paper Series).

Kripfganz, S. (2019). Generalized method of moments estimation of linear dynamic panel data models. London Stata Conference. http://repec.org/usug2019/Kripfganz_uk19.pdf

Kugler, A. D. (2004). *The Effect of Job Security Regulations on Labor Market Flexibility: Evidence from the Colombian Labor Market Reform* (No. 10215; NBER Working Paper Series). http://www.nber.org/papers/w10215

OECD, CAF, & SELA. (2024). *SME Policy Index: Latin America and the Caribbean 2024*. OECD Publishing. https://doi.org/10.1787/ba028c1d-en

OECD (2025). *ICT Investment (% of GDP).* OECD Going Digital Toolkit. https://goingdigital.oecd.org/indicator/30

Peteraf, M. A. (1993). The Cornerstones of Competitive Advantage: A Resource-Based View. *Strategic Management Journal*, *14*(3), 179–191. http://www.jstor.org/stable/2486921

ProColombia. (2024). *Industrial innovation* [PDF]. ProColombia. Retrieved from https://procolombia.co/system/files/2024-05/industrial_innovation_procolombia.pdf

Rodríguez-Lesmes, P., Gutiérrez, L. H., Urueña-Mejía, J. C., Ortiz, A. F., Medina Rojas, I. D., & Romero, M. (2025). The role of local promoters in helping microentrepreneurs engage in digital business training. *Eurasian Business Review*, *15*(1), 205–242. https://doi.org/10.1007/s40821-025-00293-y

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal*, *9*(1), 86–136.

Teece, D. J. (2018). Dynamic capabilities as (workable) management systems theory. *Journal of Management & Organization*, *24*(3), 359–368. https://doi.org/10.1017/jmo.2017.75

Teece, D. J. (2025). Dynamic Capabilities: Foundational Concepts. In J.-C. Spender (Ed.), *Dynamic Capabilities.* Cambridge University Press. https://doi.org/10.1017/9781009562713

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal*, *18*(7), 509–533. https://www.jstor.org/stable/3088148

Wernerfelt, B. (1984). A Resource-Based View of the Firm. *Strategic Management Journal*, *5*(2), 171–180. https://www.jstor.org/stable/2486175?seq=1&cid=pdf-

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, *126*(1), 25–51. https://doi.org/10.1016/j.jeconom.2004.02.005

World Bank. (2024). *Enterprise Surveys: Colombia 2023*. https://www.enterprisesurveys.org/content/dam/enterprisesurveys/documents/country/Colombia-2023.pdf

World Bank. (2025). *Manufacturing, value added (% of GDP)*. World Development Indicators. https://databank.worldbank.org/reports.aspx?source=2&series=NV.IND.MANF.ZS&country=COL

Appendix

Table 1a. ICT Equipment Intensity Measures by Percentiles, pooled 2012-2023

	count	p10	p25	p50	p75	p90	p95	p99
Real ICT investment[a]	97,250	0.0000	0.0000	0.0000	9049.8750	45741.9004	113083.7344	556458.6250
Log of ICT investment	97,250	0.0000	0.0000	0.0000	9.1106	10.7308	11.6359	13.2294
ICT inv/Sales	97,108	0.0000	0.0000	0.0000	0.0010	0.0030	0.0054	0.0180
ICT inv/Fixed assets	96,157	0.0000	0.0000	0.0000	0.0023	0.0086	0.0176	0.0689
ICT inv/Total inv fixed assets	65,486	0.0000	0.0000	0.0186	0.0978	0.4449	0.9065	1.0000
N	97250							

Note. ICT investment-intensity ratios by percentile, pooled 2012-2023. Source: own elaboration based on EAM (DANE).

[a]Monetary values are all in real terms (base year 2018=100) and thousands of COP.

Table 2a. ICT Equipment Intensity Measures by Percentiles Period 2 Balanced Panel (2018-2023)

	count	p10	p25	p50	p75	p90	p95	p99
Real ICT investment[a]	38,466	0.0000	0.0000	666.9250	12587.9473	63158.4766	159598.8281	683579.2500
Log of ICT investment	38,466	0.0000	0.0000	6.5042	9.4406	11.0534	11.9804	13.4351
ICT inv/Sales	38,429	0.0000	0.0000	0.0000	0.0010	0.0029	0.0050	0.0162
ICT inv/Fixed assets	38,118	0.0000	0.0000	0.0001	0.0023	0.0076	0.0148	0.0578
ICT inv/Total inv fixed assets	27,109	0.0000	0.0000	0.0184	0.0878	0.4017	0.8630	1.0000
N	38466							

Note. ICT investment-intensity ratios by percentile. Source: own elaboration based on EAM (DANE).

[a]Monetary values are all in real terms (base year 2018=100) and thousands of COP.

Table 3a. ICT Equipment Investment Intensity: Data Completeness Period 2 Balanced Panel (2018-2023)

Intensity measure	**Obs.**	**Non-missing obs.**	**Zero obs.**	**Estab. complete**	**Estab. gapped**	**Estab. missing**
ICT / fixed assets	38,466	38,118 (99.1%)	18,161 (47.6%)	6,226 (97.1%)	168 (2.6%)	17 (0.3%)
ICT / total investment	38,466	27,109 (70.5%)	7,150 (26.4%)	2,877 (44.9%)	2,983 (46.5%)	551 (8.6%)
ICT / total sales	38,466	38,429 (99.9%)	18,481 (48.1%)	6,397 (99.8%)	11 (0.2%)	3 (0.05%)

Notes. Period 2 balanced panel (6,411 establishments × 6 years = 38,466 observations). The three ratios follow the zero-denominator validation rule: the ratio is set to missing when its denominator is non-positive (a ratio above one is retained, since ICT equipment investment can exceed the denominator in a given year). "Non-missing obs." and "Zero obs." are observation counts (the zero share in parentheses is computed among non-missing observations); "Estab. complete", "Estab. gapped" and "Estab. missing" are establishment counts, classifying each of the 6,411 establishments by how many of its six years carry a non-missing ratio (six, one to five, and zero years, respectively), with percentages of all establishments in parentheses. The ICT/total-investment ratio is far gappier than the other two because its denominator (annual investment in fixed assets, a flow) is frequently zero. Source: own elaboration based on EAM (DANE).

Table 4a. Establishments by Region, pooled (2012-2023)

Department	Establishments	Percentage (%)
Bogota D.C.	3,832	35.40%
Antioquia	2,293	21.18%
Valle del Cauca	1,386	12.80%
Cundinamarca	702	6.49%
Santander	514	4.75%
Atlántico	452	4.18%
Risaralda	236	2.18%
Bolívar	189	1.75%
Caldas	183	1.69%
Norte de Santander	168	1.55%
Tolima	139	1.28%
Cauca	117	1.08%
Boyacá	94	0.87%
Meta	81	0.75%
Huila	81	0.75%
Quindío	75	0.69%
Magdalena	68	0.63%
Nariño	65	0.60%
Cesar	43	0.40%
Córdoba	34	0.31%
Casanare	25	0.23%
Vichada	24	0.22%
Sucre	23	0.21%
Total	**10,824**	**100.00%**

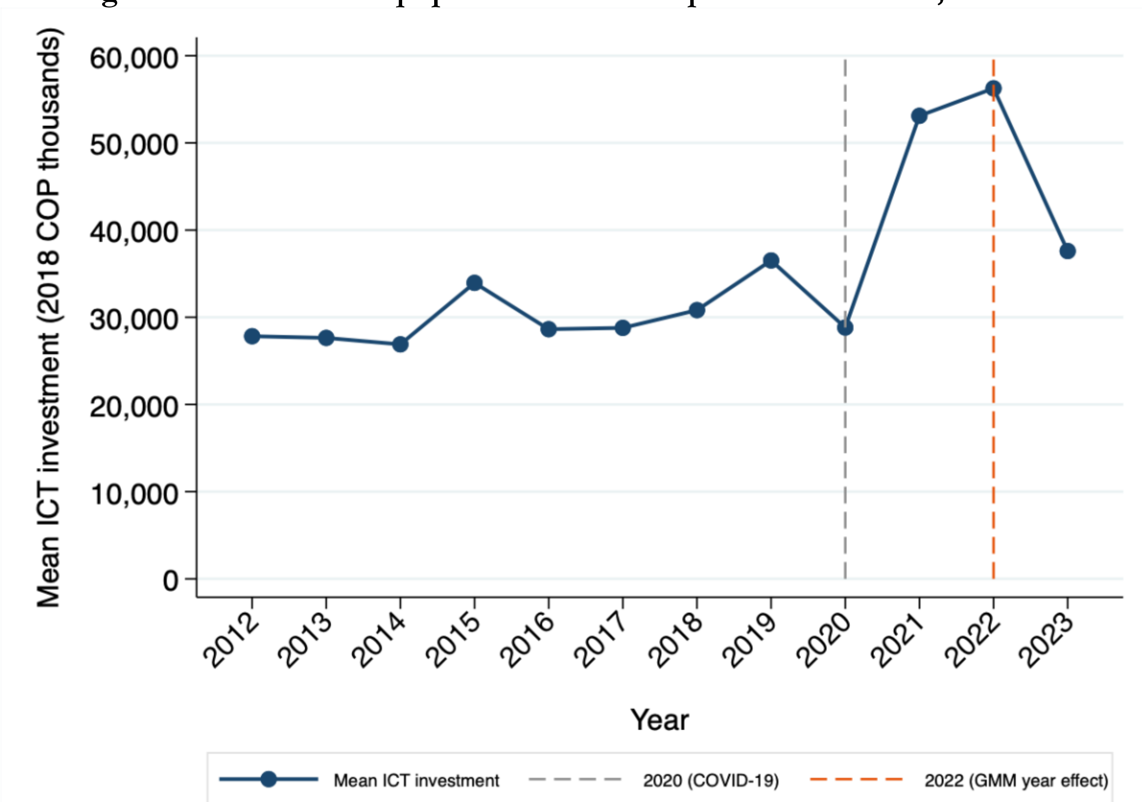
Note. Manufacturing establishments by department, pooled 2012-2023. Source: own elaboration based on EAM (DANE).

Table 5a. System GMM Sensitivity to the Difference-Equation Instrument Lag Depth (Period 2 Balanced Panel, 2018-2023)

	lag(4 5)	lag(3 5)	lag(3 4)	lag(2 3)
Log ICT Inv (t-1)	0.216	0.345	0.428	0.124
	(0.184)	(0.093)	(0.098)	(0.011)
AR(1)	0.001	0.000	0.000	0.000
AR(2)	0.402	0.013	0.002	0.075
AR(3)	0.719	0.458	0.389	0.811
Sargan/Hansen	0.181	0.100	0.148	0.000
Diff-in-Sargan/Hansen (level)	0.192	0.172	0.185	0.000
Underid.	0.455	0.000	0.000	0.000
Observations	31,996	31,996	31,996	31,996
N establishments	6,406	6,406	6,406	6,406

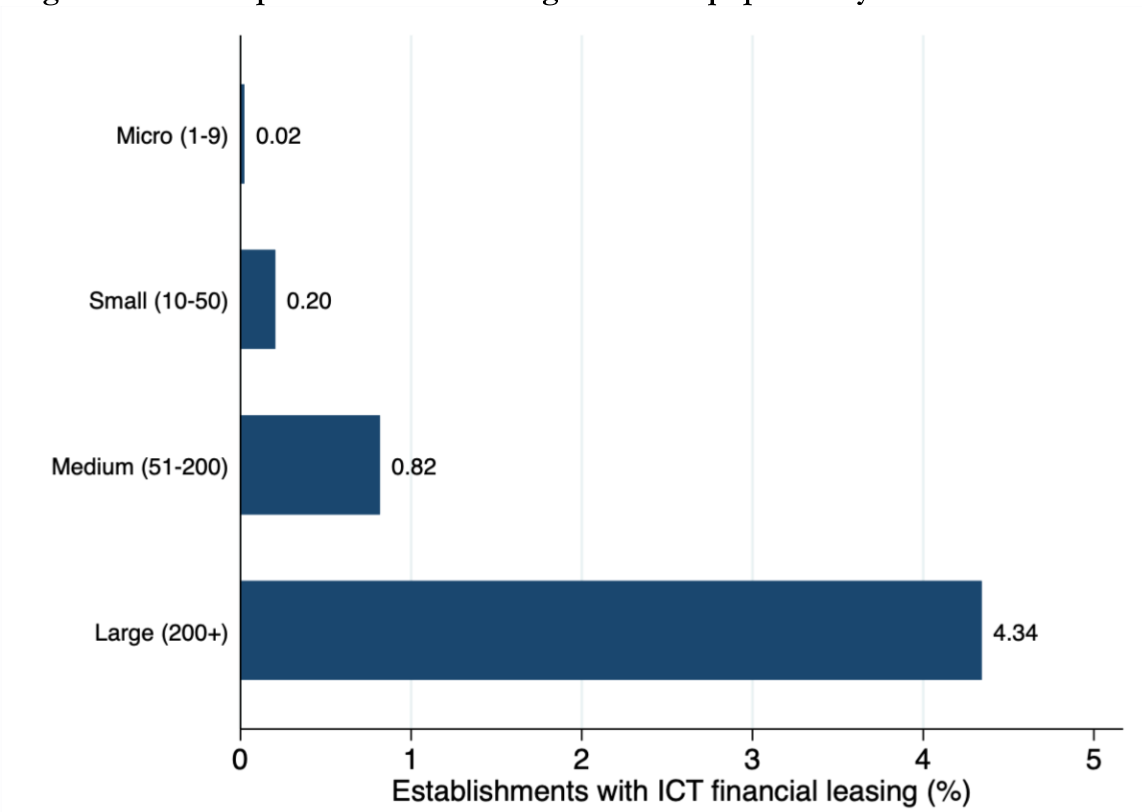
Notes. Sensitivity of the main System GMM specification (Table 5.1; Period 2 balanced panel, 6,406 establishments × 6 years = 31,996 estimation observations) to the depth of the difference-equation instruments. Across columns only the lagged levels instrumenting the differenced equation change: lag(4 5) is the main specification, then lag(3 5), lag(3 4) and lag(2 3); the level-equation (lagged-difference) instruments are held fixed at lag(3 3) for endogenous and lag(2 2) for predetermined regressors, all instruments are collapsed, and estimation is two-step with Windmeijer-corrected standard errors (in parentheses). Only the lagged dependent variable is shown; the remaining regressors (log employment, log labour productivity, export intensity, professional/technical and managerial worker shares, and year dummies) are included throughout but suppressed for brevity. Reported figures are p-values: AR(1)–AR(3) are the Arellano–Bond tests for autocorrelation of the first-differenced residuals (instrument validity requires no second-order correlation, AR(2) $p > 0.10$); Sargan/Hansen is the overidentification test and Diff-in-Sargan/Hansen (level) the incremental test of the System GMM level instruments (validity requires a high p-value); KP underid. is the Kleibergen–Paap underidentification test (identification requires a low p-value). Shortening the difference-equation lags strengthens identification (KP underid. falls from 0.455 to 0.000) but invalidates the instruments: lag(3 5) and lag(3 4) fail AR(2) (0.013 and 0.002) and lag(2 3) fails Sargan/Hansen (0.000). Only lag(4 5) satisfies AR(2), Sargan/Hansen and the level Diff-in-Sargan/Hansen simultaneously, identifying it as the shallowest valid instrument depth; the wider standard error on the lagged dependent variable is therefore an intrinsic consequence of the short (T = 6) panel rather than a remediable mis-specification. Source: own elaboration based on EAM (DANE).

Figure 1a. Mean ICT Equipment Investment per Establishment, 2012-2023



Source: own elaboration based on EAM (DANE). Full unbalanced panel, constant 2018 prices (DANE IPP Bienes de Capital, 2018=100).

Figure 2a. Take-up of Financial Leasing for ICT Equipment by Establishment Size



Note. Share of establishment-years with positive financial leasing of ICT equipment (EAM), by size tier, pooled 2015-2023 (the item is first recorded in 2015). Source: own elaboration based on EAM (DANE).