Faculty of Business Economics

Master of Management

Master's thesis

The effects of ICT adoption on productivity

Mónica Hernández Rodríguez

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Business Process Management

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Thanks to everyone who has contributed to the realization of this dream...

Thanks to that beautiful gift that life is....

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Summary

The primary objective of this dissertation is to elucidate the impact of Information and Communication Technologies (ICT) on firms' productivity. Employing a modified CDM methodology, this research establishes a correlation between a firm's innovative efforts, including investments in ICT, and the resulting outputs of product and process innovation, ultimately influencing the firm's overall productivity. To achieve the research objectives, an econometric approach was adopted, employing regression techniques such as Generalized Linear Modeling and Multiple Linear Regression to assess the effects of explanatory variables on the developed models.

The product innovation output that leads to increased sales for firms, is the improved product that already exists in the firm's portfolio (Turnimp20), resulting in an average sales increase of 7.6%. Among the seven studied process innovations, the most frequently reported was the implementation of new data processing and communication systems (Inpsict), with a frequency of 52.4%. The findings indicate a non-uniform impact of explanatory variables across different types of product innovation outputs. The effect of explanatory variables, including measures related to ICT and investments in intellectual property (IP), know-how, and patents, as well as variables associated with market research during innovation launches, did not significantly influence the developed product innovation models. The only exception was the input variable of total R&D expenses for the new product innovation in comparison to the competitor's offerings (Turmar), which yielded a negative coefficient or elasticity. Regarding the process innovation models, these explanatory variables showed significant effects in some cases or, at the very least, demonstrated positive coefficients or elasticities. This suggests a tangible effect of ICT investments in fostering process innovation outputs.

The model that best describes the relationship between productivity intensity and innovation outputs was obtained through a backward linear regression method. Notably, only six innovation outputs exhibited significant effects on the productivity intensity model. Among these outputs, three were related to product innovations and three to process innovations. The enhancement in firm productivity was more noticeable through product innovations compared to process innovations.

The main limitations of this dissertation are tied to the exploratory nature of the research and the need for more confirmatory results. Additionally, the absence of addressing endogeneity and simultaneity concerns, along with the notable collinearity among independent variables, might potentially introduce bias to the obtained results. Future research efforts should address these concerns, and longitudinal data could be employed to monitor firms' innovative efforts and outcomes. Enhanced models could be developed by considering isolated measures of ICT investments and incorporating the physical capital stock into the Cobb-Douglas production function. Exploring the effects of ICT on firms' productivity across different economic sectors, while measuring the variability in their innovative activities and financial performance outputs, offers a promising path for further research and sector benchmarking.

The adapted CDM framework has facilitated the assessment of ICT investments' impact on product and process innovation outputs, as well as firms' productivity. This framework provides a solid foundation that can be broadened in various directions.

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1 Introduction

The role of Information and Communication Technologies (ICT) in business models, performance, innovation, and productivity has been widely recognized by numerous academics and researchers (Ahn, 2002; Álvarez, 2016; Bartelsman et al., 1996; Gunasekaran & Nath, 1997; Pesole, 2015). ICT can be considered a pivotal driver of a firm's capacity to absorb innovation (Najafi-Tavani et al., 2018). ICT supports activities such as information gathering, data processing, faster communication, real-time production process evaluation, customer and supplier interaction, improved decision-making, and knowledge creation. This transformation has reshaped society and businesses in ways unimaginable just 50 years ago (Kretschmer, 2012).

The initial studies on the impact of ICT on productivity and economic growth did not establish a clear correlation between ICT investments and productivity growth (Spiezia, 2013). This was known as the Slow Paradox, where widespread computer usage did not seem to reflect in productivity statistics. The lack of correlation was primarily due to the inadequate measurement of ICT capital prices and quality (Spiezia, 2013). However, progress in generating and analyzing ICT data, advancements in academic and statistical research (Draca et al., 2009), and the standardization of methodologies for measuring ICT capital, have enabled the establishment of evidence linking ICT investment and productivity (Spiezia, 2013).

Nevertheless, the role of ICT adoption in a firm's innovative capacity, linked to the creation and development of new knowledge that can translate into new or improved products, processes, and organizational and managerial operations, remains an interesting research field. Understanding how and to what extent ICT usage contributes to firm performance and value creation needs further exploration. This understanding is vital for proposing effective policies to maximize the value of ICT adoption, enhance firm competitiveness, and elucidate the connections between innovative activities, productivity, and financial performance (Mairesse & Mohnen, 2010; OECD (Online service), 2009).

ICT investments can provide changes in technical or organizational factors, reducing the amount of input required to produce a unit of output, thereby changing the total factor productivity (TFP)(Mohnen, 2019b). Various input technological parameters, including research and development (R&D), patent acquisitions, and innovation expenditures, are associated with innovation and productivity growth (Mohnen, 2019b). However, to enhance the value of ICT investments, firms need to make complementary investments. They must restructure their operating systems to leverage the benefits of digital technologies and invest in business organization, human capital, and intangible assets (Mohnen et al., 2018a; Spiezia, 2013).

ICT's impact on firms' innovation output can be evaluated directly. This contribution can be broken down into different components, such as patented developments, the number of employees with higher education degrees relative to total employment (skill absorption), sales of high and medium technological products or knowledge-intensive services, and employment in rapidly growing firms in innovative sectors (Pesole, 2015).

Guidelines for collecting data and information about firms' innovative activities have been established through the Oslo Manual. This manual includes innovation degrees and questions related to effects and obstacles for innovative activities (OECD & Eurostat, 2018). The most widely applied technique for measuring the impact of ICT on productivity and economic growth is growth accounting (Spiezia, 2013). Growth accounting can be categorized into two branches: non-parametric and parametric approaches. The non-parametric approach assumes the elasticity of each independent variable or input to be equal to its share in value added, based on several assumptions and hypotheses regarding production technology and firm behavior. The parametric approach evaluates input elasticities using econometric techniques, avoiding prior assumptions about firm technology and behavior (Spiezia, 2013). This technique allows for the analysis of firm data and the derivation of functional relationships among variables, offering insights into the link between independent input parameters and firm productivity, and potentially even firm financial performance.

One of the most utilized frameworks for empirically explaining firms' productivity and innovation output is the CDM model (Lööf et al., 2017; Mairesse & Mohnen, 2010). Developed in 1998 by Crepon, Duguet, and Mairesse (Crepon et al., 1998), the CDM model consists of three equations that link R&D, innovation output, and productivity (Mairesse & Mohnen, 2010). The CDM framework is flexible and adaptable, allowing for variations such as using profitability instead of productivity (Lööf & Heshmati, 2006), considering innovation expenditures instead of R&D expenses (Janz et al., 2003a), and distinguishing between types of innovation outputs (Griffith et al., 2006; Mohnen et al., 2018b; Parisi et al., 2006). According to the literature (Lööf et al., 2017; Mairesse & Mohnen, 2010), since the CDM framework was based on data from a precursor of the Community Innovation Survey (CIS) applied in France, this methodology is one of the most widely used and suitable for research based on innovation survey data.

Research Motivation

Based on the statements made in the introduction, the aim of this exploratory dissertation is to address the primary research question:

- **How and to what extent do ICT investments and firm efforts impact their innovative capacity and productivity?**

The empirical model is based on the CDM framework, allowing for the evaluation of input elasticities of explanatory variables and the identification of links between innovation efforts and productivity using a two-step modeling approach. It's important to emphasize the exploratory nature of this research, where the results obtained could serve as a foundation for future confirmatory studies.

To address the main research question, it is subdivided into the following sub-questions:

Sub-question 1:

- **How do ICT investments and firm efforts influence product and process innovation outcomes?**

Sub-question 2:

- **What is the model that correlates innovation outcomes with firm productivity?**

To answer this question, an analysis linking financial data from firms is conducted, and the interpretation of input variables and innovative activities with firm financial performance is assessed.

The present dissertation is organized as follows: Chapter 1: Introduction, Chapter 2: Literature Review on ICT, Innovation, and Productivity to establish the State of the Art, Chapter 3: General Research Methodology, including main theoretical concepts related to the production function, econometric theory, and equations used to measure the impact of innovation efforts on productivity, Chapter 4: Presentation of research results, empirical findings, discussions, and benchmarking, Chapter 5: Conclusions and Chapter 6: Recommendations for Further Research.

2 Literature Review

2.1 Productivity

The efficiency of converting resources into outputs measured as goods and/or services can be determined through an indicator known as productivity. In a general sense, increases in productivity can be attributed to the expansion of outputs more than inputs, the presence of unused capacity in the production process, or changes in technology, processes, and management systems that can lead to efficiency improvements (Hall, 2011; Harper, 1997; Mohnen & Hall, 2013). Nowadays, additional factors such as R&D, ICT, absorption of innovative capacity, and the development of human capital foster the pursuit of productivity enhancements and facilitate their achievement (Iacovoiu, 2016; Mohnen et al., 2018a; Najafi-Tavani et al., 2018).

Productivity measurement serves as an essential indicator for evaluating the production performance of businesses, organizations, and nations. An increase in productivity translates to an upward shift in firms' execution and profits. Enhancing national productivity can lead to higher living standards by providing individuals with greater real income, thereby enabling them to enhance their welfare through the purchase of goods, services, and investments in areas such as leisure, housing, education, the environment, and development programs (Atkinson & Robert D, 2013; Draca et al., 2009; Kretschmer, 2012).

At a firm level, the welfare of productivity growth can be associated with improved wages or work conditions, higher profits and dividend allocation to the shareholders increases in tax payments to governments that finally can be used to fund social programs, and lower prices to customers. The increase in productivity helps firms to remain competitive and boost their competitiveness in the marketplace (Atkinson & Robert D, 2013; Saari, 2011; Ugur & Vivarelli, 2021). Consequently, firms are in a constant pursuit of methods to improve process and product quality, minimize downtime, and optimize inputs by implementing changes in operating methods and processes. However, one of the most effective strategies for boosting productivity is the adoption of new technologies. This might entail capital expenditures for acquiring new equipment or information technologies such as computers or software (Pilat et al., 2003; Saari, 2011; Ugur & Vivarelli, 2021).

2.2 Production function

A production function represents one of the most formal relationships between inputs and the quantity of output, serving as a means to measure productivity. This function treats inputs as if they are consumed in the production of aggregate output (Hall, 2011; Harper, 1997).

The production function, denoted as '*f*', can be expressed using a mathematical equation:

$$Y=f\,(x_1, x_2, x_3, \ldots, x_{n,t}) \qquad (1)$$

Here, *Y* represents the quantity of output, *x* denotes the quantities of inputs, and *t* serves as a time index. Productivity growth occurs when the production function *f* shifts upward over time (Harper, 1997). The production function enables the description of the mechanism of income generation in the production process, involving changes in inputs and/or productivity (Jorgenson & Griliches, 1967; Sickles & Zelenyuk, 2019).

When evaluating production or service provision, a comprehensive consideration of multiple contributing factors leads to the recognition of multi-factor productivity (MFP) or total factor productivity (TFP). TFP serves as a metric to quantify the incremental growth in the cumulative output of a firm or a national economy that remains unattributable to the mere summation of conventional inputs (Hall, 2011; Jorgenson & Griliches, 1967; Sickles & Zelenyuk, 2019).

The inputs of a production process can include tangible machinery and structures, land, inventories, financial assets, human capital, and intangibles such as software, patents, copyrights, brand enhancement, employee training, R&D, and organizational efforts. Intangible assets are usually more difficult to evaluate and correlate with the process output. However, they make a strong contribution to long-term productivity growth, a fact recognized by several researchers and economists (Corrado et al., 2006; Lev & Daum, 2004). Furthermore, intangible assets, especially those that facilitate enterprise innovation, could yield returns that are significantly higher than the cost of capital and the returns from fixed asset investments (Lev & Daum, 2004).

2.3 Innovation

Innovation refers to the successful adoption of a value-added novelty, leading to the initiation or enhancement of products, services, business models, markets, production methods, marketing strategies, organizational structures, management practices, or corporate frameworks (Hall, 2011; Mohnen & Hall, 2013; OECD & Eurostat, 2018; OECD & Statistical Office of the European Communities, 2005). Innovation is both a process and an outcome, driving economic and social growth (Iacovoiu, 2016; Ugur & Vivarelli, 2021). Understanding its nature, determinants, and role is crucial for assessing its impact on productivity (OECD (Online service), 2009).

Innovation can be categorized into technological innovations, which involve new products and services, and non-technological innovations, which encompass organizational or marketing changes (Mohnen & Hall, 2013). The third edition of the Oslo Manual (OECD & Statistical Office of the European Communities, 2005) recognizes four types of innovation outputs:

> "A product innovation is the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses. This includes significant improvements in technical specifications, components and materials, incorporated software, user friendliness or other functional characteristics"(OECD & Statistical Office of the European Communities, 2005, p.48).

> "A process innovation is the implementation of a new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software"(OECD & Statistical Office of the European Communities, 2005, p.49).

> “A marketing innovation is the implementation of a new marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing”(OECD & Statistical Office of the European Communities, 2005, p.49).
>
> “An organizational innovation is the implementation of a new organizational method in the firm’s business practices, workplace organization or external relations”(OECD & Statistical Office of the European Communities, 2005 p.51).

According to the Oslo Manual (OECD & Eurostat, 2018; OECD & Statistical Office of the European Communities, 2005) these definitions of innovation outputs may be subject to debate. While products are typically understood as goods or services, design modifications that do not impact the functionality of a product are categorized as marketing innovations. A new product might involve new or modified technology, as well as changes in its external appearance. Similarly, a new production method, classified as a process innovation, could necessitate a new organizational work structure within the enterprise (OECD & Statistical Office of the European Communities, 2005).

The inputs for innovation can be seen as the efforts made by firms to develop new products, new processes to generate their output, and new organizational approaches to enhance business efficiency, which can lead to the creation of new business models and the expansion or conquest of new markets (Mohnen & Hall, 2013; OECD & Statistical Office of the European Communities, 2005). One of the most significant considered inputs for innovation is research and development (R&D) expenditures (Mairesse & Mohnen, 2010). However, other intangible assets of firms, such as investments in training, acquisition of patents and licenses, market analysis, and feasibility studies, can also be considered as inputs (OECD (Online service), 2009). Innovation expenditures also encompass investments in machinery, equipment, and information and communication technology (ICT) required to develop new products or processes (Mohnen & Hall, 2013; OECD (Online service), 2009).

2.3.1 How to measure innovation?

Innovation can be assessed through either its inputs or its outputs (Mohnen & Hall, 2013). Traditional measurements of innovation encompass research and development (R&D) expenditures and patent data. R&D expenditure data has been systematically collected in numerous countries since the 1950s. On the other hand, the collection of patent data dates back much further, tracing its origins to the 19th century when intellectual property rights were established, and national patent offices were institutionalized (Mairesse & Mohnen, 2010).

R&D surveys offer insights into certain innovation inputs and are particularly valuable for assessing technology-based activities. Patent data, on the other hand, aids in comprehending specific innovation-related strategies, covering innovations that are deemed novel and significant enough to warrant patent protection (Mairesse & Mohnen, 2010; OECD (Online service), 2009).

Another valuable source for obtaining information about innovation indicators is innovation surveys. The OECD's Oslo Manual (OECD & Statistical Office of the European Communities, 2005) provides guidelines for conducting innovation surveys that gather data on innovation. This manual outlines diverse forms of enterprise innovation, methods for quantitatively measuring innovation both in terms of inputs and outputs, levels of innovation novelty, and addresses inquiries related to sources, effects, challenges, and approaches to innovation (Mairesse & Mohnen, 2010; OECD & Eurostat, 2018; OECD & Statistical Office of the European Communities, 2005).

Nowadays, numerous countries worldwide carry out innovation surveys. In Europe, these surveys are referred to as the Community Innovation Surveys (CIS) and are regularly conducted at specified intervals (Mairesse & Mohnen, 2010). Although innovation surveys were initially introduced in several European countries, their implementation has extended to other regions including Australia, Canada, Japan, Korea, Mexico, New Zealand, Norway, Switzerland, Turkey, South Africa, and the majority of Latin American countries (OECD (Online service), 2009).

Innovation surveys comprise information gathered from firms about their inputs, outputs, and the behavioral and organizational dimensions of their innovative activities. On the output side, data is collected to determine whether an enterprise has developed new products or processes, the proportion of sales attributed to significantly altered or new products (the concept of 'new' can refer to the firm, the market, or to the world). Other parameters include the inherent characteristics of innovative activities, the extent of continuous R&D efforts and/or collaboration with other entities, sources of knowledge, the motivating factors for innovation within the firm, perceived barriers, and the effectiveness of various mechanisms for facilitating innovation (OECD (Online service), 2009).

Innovation surveys have also been employed to identify the key factors driving innovation or specific modes of innovation, explore the outcomes of innovation, examine the interconnections among various innovation indicators, and analyze dynamic elements of innovation. These surveys are widely utilized by statisticians and policy analysts to benchmark and monitor innovation performance. Additionally, economists and econometricians utilize them to investigate and analyze the determinants of innovation (Mairesse & Mohnen, 2010).

Different types of data and analysis techniques serve to characterize a firm's profile, the nature of its innovative activities, and their extent. Indicators based on microdata distinguish firms based on factors like size, industry, or other specific characteristics, reflecting the practices and diversity among individual firms. Firms can vary in the kinds of innovation they pursue, whether it's process, product, organizational, or marketing innovation. Furthermore, while some firms engage in innovation, others do not. Microdata facilitates the identification of innovative profiles for firms, which can then be aggregated at the national level (OECD (Online service), 2009).

Other techniques, such as exploratory data analysis and econometrics, can also be employed. Exploratory data analysis helps identify similarities and differences in specific attributes or groups of firms. For instance, this approach might reveal correlations between in-house R&D, new-to-market product innovation, and patents, while process innovation may be closely linked with external R&D and machinery investments. Econometric techniques enable the estimation of functional relationships among variables that might vary among different groups of firms. This method could uncover, for example, that firms with higher innovation spending tend to achieve greater innovative turnover and increased productivity (OECD (Online service), 2009).

Innovation can also be assessed from the input perspective by examining the correlation between activities aimed at innovation, such as R&D, ICT investments, acquisition of external knowledge, training for new products and processes, and their subsequent introduction to the market. This approach involves evaluating the connection between measures of innovation output and productivity (Mohnen & Hall, 2013; OECD & Statistical Office of the European Communities, 2005).

The measurement of innovation aids researchers in uncovering the reasons behind a firm's innovativeness or lack thereof, and it also allows for the evaluation of innovation intensity (Mairesse & Mohnen, 2010). According to the Oslo Manual (OECD & Eurostat, 2018; OECD & Statistical Office of the European Communities, 2005), most innovation surveys measure product innovation intensity by calculating the proportion of new products in total sales over the past three years. When it comes to process innovation, some countries, following the example of the Swiss innovation survey, assess the extent of cost reduction achieved through process innovation within the same three-year period. As for the remaining innovation categories, they are typically assessed using dummy variables due to the complexities involved in measuring their specific contributions to the overall process output (Mohnen & Hall, 2013; OECD & Statistical Office of the European Communities, 2005).

2.4 The measure of innovation ICT output

The measurement of ICT innovation output can be assessed through a European Union (EU) composite output indicator. This indicator offers an estimation of output-oriented ICT innovation and encompasses both technological and non-technological facets of innovation in the field of information and communication technology (ICT), facilitating the ranking of Member States' innovation performances. The composite ICT output indicator consists of four components, outlined below (Pesole, 2015):

1. Technological innovation, quantified by patent applications. The number of patent applications per billion gross domestic product (GDP) serves as a metric for assessing an economy's ability to transform knowledge into technology (Pesole, 2015).
2. Skill absorption, measured by employment in knowledge-intensive activities. Skilled labor is crucial for effectively applying new knowledge and driving growth. This aspect reflects the structural trajectory of knowledge-intensive activities by examining the ratio of employees with higher education degrees in business industries to total employment (Pesole, 2015).
3. Competitiveness in knowledge-intensive goods and services. This measure captures the interplay between innovation and internationalization, considering the export shares of high-tech, medium-tech products, and knowledge-intensive services in a country's total product and service exports. It indicates an economy's capacity to engage in knowledge-intensive global value chains (Pesole, 2015).
4. Innovative firm dynamics, assessed by the employment of innovative fast-growing firms. This element showcases the innovativeness level of successful entrepreneurial endeavors. The statistics employ employment data from fast-growing firms, with values weighted by sector-specific innovation coefficients, designed to reflect the innovativeness of entrepreneurial sectors (Pesole, 2015).

The ICT innovation output indicator plays a crucial role in establishing correlations and assessing the contribution of ICT and its components to economic growth. This is vital for understanding variations and similarities in innovation achievements among european countries. Moreover, it equips policymakers with effective benchmarking tools to assess the effectiveness and impact of targeted interventions (Pesole, 2015).

2.5 Relation between innovation, growth, and productivity

Innovation has gained recognition from various economists and researchers as a pivotal driver for long-term economic growth (Iacovoiu, 2016; Institute of Industrial Economics of the NAS of Ukraine et al., 2019; Mohnen et al., 2018a; Ugur & Vivarelli, 2021). Solow (1956), measured the portion of growth linked to the rise in investments in machinery and related equipment. He holds the distinction of being the initial researcher to incorporate the innovation element into an economic growth model.

Investments in education and training play a pivotal role in fostering knowledge and research and development (R&D), which subsequently impact innovation capabilities, leading to enhanced productivity and competitiveness (Iacovoiu, 2016). This effect becomes especially pronounced in more advanced stages of economic development, where a firm's innovative capacities, efficient knowledge utilization, and ICT play vital roles in bolstering firm competitiveness (Iacovoiu, 2016; Mohnen et al., 2018a).

The literature (Iacovoiu, 2016), evidenced the robust connection between innovation performance and economic advancement. The study revealed that out of the 22 most developed countries examined, 19 had Global Innovation Index (GII) scores exceeding 50, and among the 23 highly developed nations, 17 achieved a GII index surpassing 40. Conversely, this index tends to be lower for less developed and developing economies.

The GII index measures the average of innovation inputs like institutions, human capital and research, infrastructure, market sophistication, business sophistication, as well as innovation outputs encompassing knowledge and technology, and creative outputs (Dutta & Lanvin, 2013).

The impact of innovation on economic growth can be understood from two endogenous perspectives: the enhanced productivity of successful innovators and the dynamics of firms, including creative destruction through entry and exit. Investment in innovation enables the achievement of higher output levels using traditional inputs of physical capital and labor. This assertion is in line with first-generation endogenous growth models, where innovation enhances growth by boosting the productivity of resources used in the production process. It also aligns with second-generation models, which emphasize that innovation leads to creative destruction and technological change, ultimately elevating firm productivity (Ugur & Vivarelli, 2021). By linking the growth rate of total factor productivity (TFP) to innovation, endogenous growth models delve into the fundamental sources of TFP growth (Diego Comin, personal communication, 2006 98 C.E.). Firms that innovate tend to experience greater profits, expand their market shares, and exhibit greater longevity compared to non-innovative counterparts (Mohnen & Hall, 2013; Ugur & Vivarelli, 2021).

2.6 ICT, growth and productivity

ICT is one of the main drivers of innovation (Pesole, 2015). ICT investments can be acknowledged as an "enabling technology" (Jovanovic & Rousseau, 2005), that has transformed firms, the economy, and society in substantial ways, and it has enhanced knowledge creation, compilation, diffusion, communication, collaboration, and information processing inside and outside firms. This empowerment enables firms to enhance their decision-making processes and streamline operations for greater efficiency, leading to reduced capital expenditures and labor costs (Arvanitis & Loukis, 2009; Brynjolfsson & Saunders, 2009; Kretschmer, 2012).

ICT capital also strengthens productivity by capitalizing on the interconnected benefits between ICT investment and other intangible assets, such as organizational capital (Brynjolfsson & Saunders, 2009). This synergy enhances the effectiveness of R&D efforts and guides the emergence of new technological innovations (Mohnen et al., 2018b). Furthermore, ICT assumes a pivotal role in facilitating a firm's knowledge acquisition through collaborative innovation networks and bolstering innovation capabilities – encompassing both product and process innovation capabilities – which have been associated with improved firm performance (Najafi-Tavani et al., 2018).

Numerous empirical studies have substantiated the positive impact of ICT investment on economic growth(Ahn, 2002; Corrado et al., 2017; F. Crespi & Pianta, 2008; Spiezia, 2013). According to O'Mahony & Vecchi (2005), which employed dynamic panel data estimation, highlighted ICT's significant role in driving economic growth. Notably, a substantial portion of total factor productivity (TFP) growth was attributed to technological advancements, particularly in the ICT-producing sectors of the United States and the United Kingdom.

Further evidence of ICT's influence on economic growth emerged from a study by Pilat et al., (2003), which evidenced rapid technological progress and competitive developments within the ICT sector. This progress led to reduced ICT prices, increased ICT applications, and broadened ICT goods and services, collectively contributing to enhanced ICT investments. Additionally, Paul Schreyer (2000), delved into the contribution of ICT to economic growth, labor, and TFP, employing a growth accounting framework across G7 countries. This framework examined ICT's role as a capital input and its impact on output growth.

However, another study conducted by Crespi et al., (2007), based on data from the Third Community Innovation Survey (CIS3) for UK firms, shed light on the interplay between ICT, organizational change, and productivity growth. The study highlighted that omitting organizational change from the analysis led to an overestimation of ICT's returns in terms of growth accounting. When organizational change is considered, the impact of ICT on productivity growth diminished, revealing a nuanced interaction between ICT and organizational dynamics.

The assessment of ICT's impact on productivity growth can be approached through either parametric or non-parametric methods. Non-parametric methods involve applying economic theory principles to empirically determine parameter values, assuming that input elasticities correspond to their shares in value added. Non-parametric approaches require the validation of neoclassical theory, where various contributing parameters are separated and represented in a production function (Kretschmer, 2012; Spiezia, 2013). On the other hand, parametric techniques utilize econometric methods to directly estimate the parameters of a production function (Kretschmer, 2012). Both parametric and non-parametric approaches will be further discussed in Chapter 3.

2.7 Innovation and productivity. Modeling approach

The majority of studies exploring the connection between innovation and productivity rely on data related to research and development (R&D), patent information, or innovation surveys (Mohnen, 2019a). Initially, early studies primarily focused on R&D capital. However, more recent investigations have incorporated firms' technological capital through variables associated with information and communication technology (ICT) (Matteucci & Sterlacchini, 2005).

The impact of R&D on productivity can be evaluated using an extended production function that includes R&D stock as an additional parameter (Ali-Yrkkö & Maliranta, 2006; Bartelsman et al., 1996; Guellec & Van Pottelsberghe De La Potterie, 2003; Ho & Wong, 2009; Koutroumpis et al., 2020). For instance, Bartelsman et al. (1996) examined the effect of R&D on productivity growth in manufacturing firms in the Netherlands. They utilized micro-level data from annual production surveys and extended R&D surveys conducted in 1985, 1989, and 1993. Using an empirical framework based on a production function, where R&D stock or knowledge capital was introduced as an additional input, the study estimated the private returns to R&D and the output elasticities of R&D stock. Various modifications to the basic R&D production function were applied to address issues such as double-counting of R&D inputs and biases from firm fixed effects. Across these different variants, the estimated output elasticity for R&D capital ranged around 6% for gross output and 8% for value added. Moreover, the calculated private rate of return to R&D was approximately 12% for gross output and 30% for value added.

Other researchers, such as Guellec & Van Pottelsberghe De La Potterie (2003), have established a positive correlation between R&D and productivity growth. Their study utilized panel data analysis from 16 OECD countries to examine the long-term impact of R&D capital stock on multifactor productivity growth over an 18-year period (from 1980 to 1998). The findings indicated that a 1% increase in business R&D led to a 0.13% rise in productivity growth. This effect was particularly pronounced in countries with a strong emphasis on business R&D and lower levels of defense-related government funding. Moreover, the results highlighted that a 1% increase in foreign R&D corresponded to a 0.44% increase in productivity growth, while a 1% rise in public R&D contributed to a 0.17% boost in productivity growth.

However, a separate study by Ali-Yrkkö & Maliranta (2006) offered different insights into the impact of R&D on productivity growth. This research focused on firm-level data from Finland and employed panel data analysis spanning nine years (from 1996 to 2004). The study investigated the influence of R&D expenditures on firms' productivity in both short-term (1-2 years) and long-term (3-5 years) contexts. The outcomes indicated that R&D had no statistically significant impact on productivity growth during the short run. Yet, over a longer time horizon (3-5 years), R&D investments did demonstrate a positive economic impact on productivity. This suggests that the effects of R&D investments may take several years, approximately five years, to become noticeable in firms' productivity measurements.

In a recent study by Koutroumpis et al. (2020), the differential impact of R&D capital on ICT and non-ICT firms was estimated. This research focused on analyzing the R&D activities of over 9000 firms across Germany, France, Sweden, and the United Kingdom during the period from 2004 to 2013. The findings revealed that, in general, R&D capital had a more significant effect on the revenues of ICT firms compared to non-ICT firms.

R&D capital plays a direct and influential role in driving firm revenues, fostering economic growth, and giving rise to innovative outcomes, including new intermediary or final consumer goods. Additionally, R&D initiatives generate spillover effects, enhancing a firm's absorptive capacity and contributing to the accumulation of knowledge that yields higher returns in the future (Mohnen, 2019a).

The simultaneous evaluation of R&D, innovation, and productivity often relies on the CDM model, as proposed by Crepon et al. (1998). This model establishes a connection between innovation inputs, primarily R&D inputs but not exclusively, innovation outputs, and productivity. The framework of this modeling approach enables us to understand the innovation process by analyzing its inputs, outputs, and their impact on firm productivity (Crepon et al., 1998; Mairesse & Mohnen, 2010).

The outcomes of the ICT innovation process can be linked to various factors, including the number of developed patents, the ability to absorb new skills and knowledge, the competitiveness of knowledge-intensive goods and services, and the dynamics of innovative firms (Pesole, 2015).

The CDM methodology follows a logical sequence based on firm decisions and the outcomes of the innovation process. It involves several steps (Mairesse & Mohnen, 2010):

1. Assessment of Innovation Efforts: The initial step examines whether firms have made efforts towards innovation and the resources they have invested in this regard.
2. Evaluation of Innovation Outputs: The second step analyzes the outcomes of the innovation process resulting from the inputs utilized.
3. Incorporation into Productivity Equation: The innovation outputs are then integrated as explanatory variables into a firm's productivity equation.

The CDM framework is well-suited for utilizing innovation survey data. This allows for the development of a comprehensive model that connects innovation inputs, outputs, and overall productivity (Mairesse & Mohnen, 2010). This framework also provides flexibility in measuring various aspects of different innovation approaches. It addresses challenges related to selection and simultaneity in the innovation process and aids in benchmarking the productivity-related performance of innovation outputs across different studies. Moreover, the CDM model can be applied to both binary and continuous data and can accommodate various sources of innovation (Mohnen, 2019a).

Mairesse et al. (2005) conducted a study to assess the robustness of the CDM framework. In this research, they examined how sensitive the estimated productivity elasticities of innovation and R&D were to various model specifications and estimation methods. To do this, they used data from the 1998-2000 French Community Innovation Survey.The results of the study demonstrated that the

CDM model provided reliable insights into the magnitudes of the rates of return to R&D, which were estimated through an extended Cobb-Douglas production function. This held true when issues related to endogeneity and, in certain cases, selectivity were appropriately addressed. The estimates were also consistent across different measures of product innovation, encompassing both new-to-firm and new-to-market product, process, and patent innovations. While the combination of innovation surveys and the CDM model offers valuable insights into firms' R&D and innovation activities, it's important to take into account the quality of the data and the relevance of the analysis. This consideration highlights the significance of ensuring the accuracy and appropriateness of both the data collection process and the analytical methodologies used.

The CDM framework has been applied in various contexts. Parisi et al. (2006) conducted a study using this framework to investigate the effects of both product and process innovation on firm productivity, as well as the roles of R&D and fixed capital investment in the likelihood of innovation at the firm level. Their research was based on a database of firm-level data from Italy. The findings of the study revealed that process innovation exerts a more substantial impact on firm productivity compared to product innovation. The study also highlighted the relationship between R&D expenses and the probability of introducing a new product. Additionally, the research indicated that fixed capital investment plays a role in fostering the likelihood of process innovation. This might be explained by the fact that new processes and techniques often involve the utilization of new investment goods. Interestingly, the study showed that R&D expenses positively influence the probability of process innovation through an increase in fixed capital investment. This suggests that R&D activities enhance the absorption of new technologies, which subsequently contribute to an improvement in firm productivity. In essence, the research indicated the interconnectedness between R&D, capital investment, innovation, and overall firm performance.

Regarding the influence of ICT and complementarity effects on firm performance, Polder et al. (2009) conducted a study that delved into various modes of innovation and their impact on productivity. Their approach utilized an extended CDM framework featuring two equations for innovation inputs (R&D and ICT) and three equations for innovation outputs (product, process, and organizational innovation), all of which were subsequently correlated with a productivity equation. The study drew data from surveys conducted by Statistics Netherlands and linked the information at the firm level.

The findings of the study revealed several key insights. In the manufacturing sector, R&D demonstrated a positive effect on product innovation, while no significant evidence was found for process or organizational innovation in the same sector. However, organizational innovation emerged as the most influential factor on firm productivity, being the only innovation mode that led to higher Total Factor Productivity (TFP) levels. Moreover, when considering product and process innovation, higher TFP levels were achieved only when accounting for organizational innovation. This indicates the importance of incorporating non-technological innovation when examining the impact of innovation on firm productivity.

Additionally, the study shed light on the role of ICT investments. It highlighted that ICT investments had a stronger influence on enhancing innovation, particularly for both service and manufacturing firms. This emphasizes the significant role of ICT in fostering innovation across various industries.

In a separate study conducted by Hall et al. (2013), a similar approach based on the modified CDM model yielded outcomes consistent with those of the Polder et al. (2009) research. The study was developed using a large unbalanced panel data sample of Italian manufacturing firms (1995-2006 period), based on a four consecutive Survey on Manufacturing Firms. The study focused on examining the interrelationships between process, product, and organizational innovation, along with productivity, at the firm level. Both R&D and ICT were used as explanatory variables within the model. The results revealed that these variables had a direct impact on productivity while also exerting an indirect influence through the innovation equation. Interestingly, R&D exhibited a stronger impact on innovation, whereas ICT had a more pronounced effect on productivity. R&D and ICT were neither complements nor substitutes. The authors explained this observation by pointing out the distinct channels through which each variable contributes to firm innovation and productivity. R&D activities were associated with the development of intangible assets, whereas ICT was closely intertwined with technological advancements, essentially becoming an integral part of the transformation process. Overall, the research further emphasized the complexity between innovation, R&D, ICT, and firm productivity, highlighting their distinct roles and pathways of influence.

Mohnen et al. (2018a) also explored the complementarities among different innovation modes in their research. In contrast to a CDM model approach, they adopted a different methodology to examine the relationships between ICT, technological innovation, and non-technological innovation. They took into account the direct impact of R&D on both the production function and innovation output. In their model, ICT, R&D, and organizational innovation were treated as binary choices with reciprocal feedback effects. Rather than combining ICT, R&D, and organizational innovation into a single model, these variables were considered separately as distinct types of capital, aligning with the findings of Hall et al. (2013). This approach recognized that R&D and ICT contribute to firm innovation and productivity through unique channels. The study drew data from the Business Register and various surveys conducted by Statistics Netherlands. Information on R&D, organizational innovation, and export status was obtained from the Community Innovation Survey, while details about ICT investment were sourced from the investment survey, focusing specifically on hardware.

The outcomes of the research indicated that simultaneous investments in ICT, R&D, and organizational innovation are advantageous for firms. These three types of investments were found to be complementary, with the probability of investing in one positively influencing the likelihood of investing in the others. Notably, when considered together, the growth in Total Factor Productivity (TFP) exceeded that resulting from individual or paired investments, except for the combination of ICT and organizational innovation. However, this specific combination yielded a coefficient that was neither significant nor as substantial as the others. The authors suggested that this outcome might be due to their focus solely on hardware investment and proposed that the complementarity between ICT and organizational innovation might be more relevant to software and other communication tools.

Interestingly, the study unveiled a significant and robust complementarity between R&D and organizational innovation, with the maximum α coefficient achieved for this combination. This finding hinted at a strong synergy potentially attributed to the introduction of knowledge management systems, improved information flows, coordination and collaboration efforts, thereby supporting the notion of ICT as a general-purpose technology (Jovanovic & Rousseau, 2005).

Research on firm innovation has extended its scope to various domains, including employment growth(Hall et al., 2008; Harrison et al., 2014). Harrison et al. (2014) assessed the impact of both process and product innovation on employment growth. The study utilized comparable firm-level data from France, Germany, Spain, and the United Kingdom. It correlated employment growth with sales of old and new products, employing a two-goods production function and an employment equation. The findings reveal that process innovation displaces employment in manufacturing, but to a lesser extent in the service sector. In both cases, compensation effects are dominant, and there is a correlation between product innovation and employment growth. Hall et al. (2008) employed a similar methodology and obtained similar findings for Italian manufacturing firms.

Other factors influencing labor productivity growth, such as the impact of demand and innovation, have also been explored (Crespi & Pianta, 2008). In their study, Crespi & Pianta (2008) introduced a new set of models that combined the analysis of demand and technological factors to explain labor productivity growth in both European manufacturing and service industries. They used data from the SIEPI-CIS2 database and Eurostat Input–Output data at the industry level, covering 22 manufacturing sectors and 10 services sectors across Germany, France, Italy, the Netherlands, Portugal, and the United Kingdom.

The results highlighted the existing complementarities between technological factors and demand dynamics in driving productivity growth. The mechanisms driving firm-level productivity growth varied based on the firm's orientation towards product or process innovation. According to the study, innovation in firms was associated with two distinct strategies: technological competitiveness, characterized by knowledge generation, product innovation, and expansion into new markets; and cost competitiveness, involving job and labor-saving measures, flexibility, and restructuring.

Numerous studies have examined the nature of innovation across European countries, establishing connections between innovative practices, firm or market attributes, and highlighting the significant impact of innovative activities on productivity (Griffith et al., 2006; Hall et al., 2008; Janz et al., 2003b; Masso & Vahter, 2012; Matteucci & Sterlacchini, 2004). Janz et al. (2003b) investigated the characteristics of innovative firm performance in Germany and Sweden. The findings revealed that larger firms had a higher likelihood of being innovative, and global competition played a role in encouraging product innovation. Firms engaged in international trade were more likely to develop new products compared to those primarily operating in local markets. Similar conclusions were obtained by Hall et al. (2008), who found that international competition contributed to higher R&D intensity, especially for high-tech firms. Firm size and R&D intensity, combined with investments in machinery, were associated with increased probabilities of both process and product innovations.

Griffith et al. (2006) conducted a comparative analysis of the role of innovation in France, Germany, Spain, and the United Kingdom by examining the relationship between R&D expenditure, innovation output, and productivity. The empirical findings revealed a consistent framework driving innovation and productivity across these countries, while also highlighting some distinct differences. R&D investments were found to increase the likelihood of both process and product innovations. The importance of formal protection for process innovation was found to be lower than for product innovation. Supplier information played a crucial role in process innovation, whereas customer information had a more significant impact on promoting product innovation. Interestingly, competitors had a lesser influence on the innovative process compared to suppliers and customers. The study also revealed non-uniform results in terms of labor productivity among the four countries. Process innovation was associated with improved productivity in France, while product innovation contributed to higher productivity in Spain, France, and the United Kingdom, but not in Germany.

Matteucci & Sterlacchini (2004) studied the connection between technological capital and productivity by analyzing R&D and ICT measures using data from the Capitalia survey for a longitudinal sample of Italian firms over the period 1998-2000. The study revealed that both R&D and ICT exerted a positive influence on changes in Total Factor Productivity (TFP). Notably, the impact of ICT intensity becomes significant when a lag is introduced. Moreover, the study indicated that the predicted rate of return for ICT investments surpasses that of R&D. This suggests that to maximize the benefits of ICT investments, they should be accompanied by complementary investments in intangible assets and organizational changes.

Innovation research has extended to Latin American countries as well (G. Crespi & Zuniga, 2012; De Fuentes et al., 2015; Monge-Gonzalez & Hewitt, 2010; Raffo et al., 2008). De Fuentes (2015) delved into the factors influencing innovation and productivity in Mexico's service sector, using data from the Mexican Survey on Innovation and Technology Development. The findings indicated that while manufacturing firms in Mexico possess more developed innovation processes, service firms also participate in innovation activities, resulting in improved performance and enhanced productivity.

Similarly, Crespi & Zuniga (2010) examined the determinants of technological innovation and its impact on labor productivity in Argentina, Chile, Colombia, Costa Rica, Panama, and Uruguay, utilizing microdata from innovation surveys. The study reinforced the role of innovation in enhancing firms' economic performance in Latin America. However, it also highlighted that the factors driving innovation in firms exhibit more significant heterogeneity compared to OECD countries.

Another study (Raffo et al., 2008) conducted a comparison of the roles of innovation and economic performance between European and Latin American countries. This analysis utilized firm-level data from France, Spain, Switzerland, Argentina, Brazil, and Mexico. The overall results showed that firms engage in innovation activities to enhance their economic performance in both regions. However, firms in developing countries face more challenges in establishing effective innovative networks and interacting with the national system. This hinders their ability to leverage information and knowledge for increased R&D investments.

In a related study, Monge-Gonzalez & Hewitt (2010) explored the connections between innovation, R&D, and productivity in domestic ICT firms in Costa Rica. The findings revealed that while most firms are involved in innovation activities, their focus appears to be more on maintaining or expanding their market share rather than enhancing productivity. Interestingly, approximately half of these firms do not protect the intellectual property resulting from their innovative efforts.

Innovation research has primarily relied on an output-based methodology (Griffith et al., 2006; Hall et al., 2013; Masso & Vahter, 2012; Polder et al., 2009). This shift in approach stems from challenges in fully capturing all dimensions of innovation inputs, leading to potential underestimation of the impact of innovation on productivity. The output-based approach emphasizes the outcomes of activities such as R&D, training investments, adoption of new technologies, or sales of new products. These aspects may not be easily quantifiable using the input approach, given the presence of unobservable variables.

The majority of innovation studies have primarily utilized cross-sectional data (Mohnen & Hall, 2013; Morris, 2018). This choice is primarily attributed to the nature of the Community Innovation Survey, which gathers information on firms' innovative activities within a timeframe of up to three years prior, and often lacks repeated observations for many firms. This allows for unobserved heterogeneity among firms (Morris, 2018). To tackle this challenge, Morris (2018) explored the relationship between innovation and productivity across diverse firms using a large cross-country panel dataset, drawing on data from a total of 40,577 small, medium, and large firms surveyed in the World Bank Enterprise Surveys (WBES). The findings suggest that studies based on cross-sectional data may exhibit an upward bias. Nonetheless, it is revealed that innovative firms exhibit higher productivity levels in both manufacturing and service sectors. Furthermore, tangible and intangible investments in innovative activities play a critical role in fostering both product and process innovation, thereby contributing to enhanced firm performance.

Innovation studies have also extended to the regions of Asia and Africa (Ben Khalifa, 2023; Zhu et al., 2021). Zhu et al. (2021) investigated the influence of R&D and ICT on firm productivity using data from the World Bank innovation survey. The results support the notion that both R&D and ICT investments have a positive impact on productivity. These variables contribute to better resource allocation and increased innovation output. However, the decisions to invest in ICT are primarily guided by technological factors like foreign technology, standardization, and investments in new machinery or equipment. On the other hand, R&D investment decisions are also influenced by factors such as capital intensity, enterprise size, exports, and labor quality. Notably, R&D investment intensity exhibited a stronger impact on product and process innovation compared to ICT investments. These findings align with the results of Hall et al. (2013), indicating that R&D has a more pronounced effect on innovation, while ICT influences productivity. Specifically, a 10% increase in R&D input led to a 1.507-unit increase in product innovation output and a 1.645-unit increase in process innovation output. In contrast, a 10% increase in ICT input resulted in a smaller increase of 0.875 units for product innovation and 0.730 units for process innovation.

Khalifa (2023) conducted a study on the impact of R&D and ICT on innovation and productivity in Tunisian manufacturing firms. The empirical analysis utilized cross-sectional data collected in 2016 by the Tunisian Institute of Competitiveness and Quantitative Studies. The findings revealed a positive relationship between R&D, ICT, and firm's innovative capacity. Consistent with the findings of Polder et al. (2009), R&D emerged as a significant predictor of product innovation but not process innovation. On the other hand, ICT showed a positive correlation with both types of innovation, with a stronger influence on process innovation. The study also highlighted a complementary relationship between R&D and ICT investments. Firms that combined R&D and ICT usage were more likely to introduce new products or develop process innovations.

In terms of firm characteristics leading to engage in R&D activities, the author concluded that the probability increases with firm size, access to training programs and public funds, as well as being part of a business group. Valuable information from suppliers and firm customers played a pivotal role in promoting R&D activities. Interestingly, participation in the international market was negatively associated with R&D activities. This unexpected result was attributed to survey specifics, where many exporters acted as subcontractors for foreign firms, limiting their engagement in R&D. However, among exporting firms that did engage in R&D, there was a higher likelihood of increasing R&D expenditures.

A different approach to innovation studies was developed by Uyen et al. (2010). The authors examined the relationship between innovation and productivity by specifying ICT indicators (intranet, extranet, video-conference, electronic forum, group project, e-commerce, and software to manage orders) and types of R&D activities (internal or external), instead of using their aggregated measures. The research was based on two large and nationally representative datasets of Luxembourg manufacturing and service firms, drawn from the Community Innovation Survey and the annual ICT Usage and E-commerce in Enterprises Survey. The combined data allowed the evaluation of different ICT capital stocks in determining technological and non-technological innovation outputs. The CDM model was adapted, considering a four-equation model that links labor productivity to innovation outputs, innovation outputs to R&D and ICT, and R&D and ICT to their contributing factors.

The findings revealed that internal and external R&D expenses have a higher impact on fostering technological innovation, such as product innovation and/or innovative performance, while external R&D only promotes process and organizational innovation. The results for the different ICT indicators are debatable. ICT internal communication tools, such as electronic group projects, lead to an increase in the probability of introducing a new product, process, and organizational innovation. Intranet and e-commerce were highly correlated with product innovation and innovative performance, but they had no effect on process and organizational innovations, and the likelihood of having a product innovation is lower for firms adopting extranet. Also, the electronic forum had a negative effect on process innovation. These controversial results were explained by the fact that ICT investments can substitute other forms of capital, and in the short term, can lead to a decrease in innovation activities. Regarding labor productivity, this was positively correlated with technological and non-technological innovation output. Organizational innovation enabled by adequate ICT tools leads to an improvement in products, services, cost reduction, and transaction times, resulting in enhanced labor productivity.

Most of the studies concerning innovation and productivity suffer from a significant drawback - the absence of successive measurements of firms' innovative activities. This limitation restricts the observation of firms over time and necessitates the use of dummy variables to measure innovative performance. This issue could be addressed through the utilization of longitudinal data and innovation indicators linked with firm financial performance, such as the share of sales from new products or cost reduction due to the application of new processes. Despite these limitations, micro-data or firm-level studies have provided valuable insights into the impact of R&D and ICT on firm innovative activities and productivity. These studies enable the measurement of the output elasticity of these explanatory variables and their contribution to firm performance.

In general, the research evidence demonstrates a positive impact of R&D and ICT investments on firm performance and has allowed for the correlation of these variables with specific innovative activities. In most cases, R&D has a higher impact on product innovation (Parisi et al., 2006), while ICT is more influential for process innovation (Khalifa, 2023). However, R&D also enhances the likelihood of acquiring new technologies, thus improving the probability of process innovation (Parisi et al., 2006), and ICT, as indicated in other studies (Polder et al., 2009; Uyen et al., 2010), enhances both product and process innovation. In general, both R&D and ICT exhibit a positive impact on total factor productivity (TFP) change.

The original CDM framework provides a satisfactory evaluation of the impact of R&D and ICT on firm productivity. It offers a structural model that can be expanded in various directions, such as examining employment growth (Hall et al., 2008; Harrison et al., 2014), assessing the impact of demand (Crespi & Pianta, 2008), and considering firm and market characteristics (Janz et al., 2003b). This framework offers a high degree of flexibility and the potential to understand firms' innovative activities, establish relationships between explanatory variables and firm productivity and financial performance, and measure complementarities among different modes of innovation. Furthermore, the CDM framework facilitates benchmarking of innovative activities among firms and countries.

3 Empirical Methodology and Related Theory

3.1 Empirical methods: Parametric and non-parametric approach

The main methodologies for evaluating the impact of ICT on firm productivity and growth can be subdivided into parametric or non-parametric approaches. Non-parametric approaches are mostly based on growth accounting, and they empirically determine the parameters of a production function using specific index numbers. To achieve this, the neoclassical assumptions of constant scale economies, perfect competition, and zero profits should be valid. The productive process is represented through a production function measured in volumes. Firm growth can be represented by input growth, which separates different types of capital, including ICT and non-ICT capital. The inputs are primarily weighted based on their income shares, which approximately represent production elasticities. This methodology allows for a relatively simple evaluation of the sources of output and productivity growth. However, it doesn't reveal causal relationships and equates the input weights to their revenue shares, assuming perfect competition and constant returns to scale (Kretschmer, 2012).

The parametric method relies on econometric approaches and does not assume that the elasticity estimations of the inputs are equal to their income shares, considering perfect competition. Instead, based on econometric techniques, it determines whether the input or explanatory variable significantly contributes to explaining productivity growth. This technique also allows distinguishing between ICT and non-ICT capital as inputs in the production function. However, as ICT is not exogenous, this decision is tied to output and productivity. Therefore, it is important to conduct robustness checks and assess causality (Kretschmer, 2012). Parametric and non-parametric methodologies should be considered complementary. Non-parametric techniques can provide a benchmark for examining complex results obtained from the parametric method (Spiezia, 2013).

3.2 Cobb-Douglas production function augmented with knowledge capital

The effect of innovation on economic growth can be explained by endogenous models, wherein the increase in both physical and non-physical capital investment leads to an increment in the marginal product above the discount rate. Another perspective suggests that technological investment enhances production efficiency by reducing costs, improving product quality, or achieving both objectives (Ugur & Vivarelli, 2021).

In any case, the impact of innovation on productivity can be captured using a Cobb-Douglas production function augmented with knowledge capital (i.e., investment in innovation). This parameter serves as an additional input enabling the firm to achieve higher outputs with specific levels of physical and labor inputs (Ugur & Vivarelli, 2021).

Based on Griliches (1979) framework for quantifying knowledge capital and the research by Ugur & Vivarelli (2021), the augmented Cobb-Douglas production function, incorporating knowledge capital under the assumption of perfect competition, can be expressed as follows:

$$Q_{it} = Ae^{\lambda it} \cdot C_{it}^{\alpha} \cdot L_{it}^{\beta} \cdot K_{it}^{\gamma} \cdot e^{u_{it}} \qquad (2)$$

Here, all variables are expressed for each firm *i* and time *t*. *Qit* represents the total output of the firm, *Cit* is the physical capital stock; *Kit* and *Lit* are the R&D knowledge and labor capital, respectively, and A$e\lambda it$ represents technological progress with a rate of disembodied technological change λ . The coefficients α, β and γ denote the elasticities for the respective capital types. Additionally, $e^{u i_t}$ represents other unmeasured components affecting output and productivity (Ugur & Vivarelli, 2021).

3.3 CDM modeling equations

The CDM model, developed by Crepon et al. (1998), represents an advancement of the Griliches-type knowledge capital model. The CDM methodology encompasses firm decisions related to innovative activities and their intensities, while addressing endogeneity and simultaneity challenges within the modeling process. The simplified set of equations (omitting time *t* for simplicity) includes: a) the firm's probability of engaging in innovative activities and their intensity (equations 3-4), usually but not limited to R&D expenses, y_{1i}, b) the equation for innovation output (equation 5), wherein R&D is among the determining factors, c) the productivity equation (equation 6), influenced by innovation output and other explanatory variables (Mohnen & Hall, 2013; Ugur & Vivarelli, 2021).

$$y_{0i} = \begin{cases} 1 \ if \ y_{0i}^* & = X_{0i}\beta_0 + \varepsilon_{0i} > 0 \\ 0 \ if \ y_{0i}^* & = X_{0i}\beta_0 + \varepsilon_{0i} \leq 0 \end{cases} \qquad (3)$$

$$y_{1i} = y_{1i}^* = X_{1i}\beta_1 + \varepsilon_{1i} \ if \ y_{0i} = 1 \qquad (4)$$

$$y_{2i} = \alpha_{21}y_{1i} + X_{2i}\beta_2 + \varepsilon_{21i} \ if \ y_{0i} = 1 \qquad (5)$$

$$y_{3i} = \alpha_{32}y_{2i} + X_{3i}\beta_3 + \varepsilon_{32i} \ if \ y_{0i} = 1 \qquad (6)$$

Where y_{0i} indicates whether the firm is engaged in innovative activities or not, y_{1i} represents the intensity of R&D innovative activity, y_{2i} and y_{3i} quantify innovation outputs and productivity, respectively. X_{0i}, X_{1i}, X_{2i} and X_{3i} are vectors of explanatory variables, while $\varepsilon's$ represents the error terms. The vectors $\alpha's$ and $\beta's$ denote the sets of unknown parameters (Mohnen & Hall, 2013; Ugur & Vivarelli, 2021).

The CDM methodology facilitates the elucidation of the selectivity of R&D and/or innovators, as represented in equation 3. In its early form, the model was assessed using techniques such as asymptotic least squares or minimum distance estimators, with simultaneous estimation of all equations. However, contemporary research utilizing the CDM methodology often adopts a sequential approach, where the predicted value of one endogenous variable is integrated into the estimation of the next equation. Furthermore, this approach incorporates a correction factor and considers the estimation of standard errors to address potential selection bias issues (Mohnen & Hall, 2013).

3.4 Econometric modeling. A short overview

According to the literature (Spanos, 1986) "Econometrics is concerned with the systematic study of economic phenomena using observed data." The distinct characteristic that sets econometrics apart from other economic methods is its utilization of observed data to analyze economic aspects.

The econometric, or parametric, approach employs empirical measurements to elucidate economic relationships. Its foundation rests upon economic theory, economic data, and statistical methods. Over the last 50 years, this methodology has witnessed significant growth, driven by advancements in computing technology and the increased availability of micro-level data. These developments have enabled the evolution of panel data methods (Baltagi, 2008).

3.4.1 Economic data and the sampling model

Economic data often lacks an experimental nature and can manifest in one of three primary forms, as outlined by Spanos (1986):

1. Time series: This type of data measures a specific variable at sequential points in time (e.g., annually, quarterly, monthly, or weekly).
2. Cross-section: In this form, data measures a particular variable at a specific moment in time across different units, such as individuals, firms, or industries.
3. Panel data: This type refers to cross-sectional data collected over multiple time periods.

To derive accurate insights from the employed data, an econometric modeler must understand the data's collection methodology and the precise variables it measures. This knowledge enables the modeler to select an appropriate sampling model and establish connections between the proposed econometric model and the associated economic theory (Spanos, 1986).

For instance, when employing cross-sectional data through a simple random sampling method (where each unit in the population has an equal chance of being selected), the random sampling model appears to be the most fitting option. However, if a stratified sampling method (dividing the population into distinct groups or strata) is used, an independent sampling model might be more appropriate. In the case of time-series data, selecting between a random or independent sampling model is often unrealistic, and a non-random sample model appears to be the most suitable approach (Spanos, 1986).

3.5 Regression analysis

Regression analysis serves as a valuable statistical tool for investigating relationships among variables. It aids in uncovering the causal effects of one or more variables on others. Researchers utilize regression techniques by analyzing data pertaining to variables of interest, allowing them to quantify the impact of independent variables on the influenced variable, also known as the dependent variable (Sykes, 1993).

During the estimation process, the statistical significance of the relationships among variables is evaluated. This assessment helps establish the level of confidence in the estimated relationship's accuracy compared to the actual relationship. Regression analysis has played a central role in econometric methods, acting as a fundamental tool for understanding these relationships (Sykes, 1993).

3.5.1 Linear regression model. Specification, estimation and assumptions

A linear relationship between a depend variable Y_i and an independent variable X_i can be represent as follows (Baltagi, 2008):

$$Y_i = \alpha + \beta X_i + u_i \qquad i = 1, 2, \ldots, n \qquad (7)$$

Here, Y_i signifies the i-th observation on the dependent variable Y, while X_i represents the i-th observation on the independent variable X. The variable n denotes the number of observations, which could equate to the number of firms in a cross-section or the count of years if observations are gathered annually. The parameters α and β correspond to the intercept and slope, respectively, in the linear equation connecting Y and X. These parameters are unknown and are estimated from the data. The error term is u_i, a random variable embodying the unexplained variability in Y that exists beyond the linear relationship between X and Y (Baltagi, 2008).

The parameters α and β can be estimated by the best fitting line through the data. With this understanding, equation 7 can be rewritten as follows (Baltagi, 2008):

$$\hat{Y}_i = \hat{\alpha} + \hat{\beta} X_i \qquad (8)$$

Here, the symbol ^ represents an estimation of the respective parameter. Each observation (X_i, Y_i) is accompanied by an associated observable error, which is represented by the equation: (Baltagi, 2008):

$$\varepsilon_i = Y_i - \hat{Y}_i \qquad (9)$$

As a consequence, while the u_i's values remain unobservable, the ε_i's values are observable, with each of the n errors corresponding to a distinct observation (Baltagi, 2008).

When assessing more than one independent variable X in relation to the dependent variable Y, the approach is referred to as multiple regression analysis. This technique facilitates the simultaneous evaluation of the combined impact of multiple variables on a single dependent variable. The initial model (equation 7) can be adapted and presented as (Sykes, 1993):

$$Y_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_p X_{pi} + u_t \qquad i = 1, 2, \ldots, n \qquad (10)$$

In this context, β_1, β_2,… β_p represent the coefficients associated with the independent variables X_1, X_2,… X_p across i observations.

When conducting a multiple regression analysis involving p explanatory variables, the objective is to estimate an equation within an p-dimensional 'hyperplane' in order to minimize the sum of squares. The intercept represents a general constant term, and each slope within its dimension represents a distinct regression coefficient (Sykes, 1993). Similar to simple regression analysis, it is possible to estimate the error by computing the difference between the actual Y_i and the estimated values ($\hat{Y}_i$). The sum of squares of these errors terms serves as a metric to quantify the degree of misfit exhibited by the model. The process of estimating α and β involves minimizing this measure of misfit. Indeed, the least square method minimize the residual of sum squares given by (Baltagi, 2008):

$$SSE = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} \left(Y_i - \hat{\alpha} - \hat{\beta} X_i\right)^2 \qquad i = 1, 2, \ldots, n \qquad (11)$$

Whit $\varepsilon_i = Y_i - \hat{\alpha} - \hat{\beta} X_i$ (12), $i = 1, 2, \ldots, n$, and $\hat{\alpha}$ and $\hat{\beta}$ denoting the estimated values of α and β, respectively. These estimated values are the solutions of the two firs-order conditions (Baltagi, 2008):

$$\partial\left(\sum_{i=1}^{n} \varepsilon_i^2\right)/\partial\alpha = -2 \sum_{i=1}^{n} \varepsilon_i = 0 \qquad (13)$$

$$\partial\left(\sum_{i=1}^{n} \varepsilon_i^2\right)/\partial\beta = -2 \sum_{i=1}^{n} \varepsilon_i X_i = 0 \qquad (14)$$

Solving the represented equations for α and β, its possible to obtain $\hat{\alpha}_{OLS}$ and $\hat{\beta}_{OLS}$, where OLS denotes the ordinary least squares estimators (Baltagi, 2008).

The total sum of squares (SST) quatifies the total variation in the dependent variable and can be descomposed as the sum of the sum of suquares of the erros (SSE) and the sum of squares of the regression (SSR).

According to the literature (Baltagi, 2008), specific assumptions about the model need to be imposed in order to study the statistical properties of the OLS estimators for α and β. These assumptions are commonly known as the Gauss-Markov conditions or the classical linear regression assumptions. They establish the Ordinary Least Squares (OLS) estimator as the Best Linear Unbiased Estimator (BLUE):

1. The assumption of a zero mean: The error of (u_i) is a random variable with mean or expected value of zero. *E* (u_i)=0 for every *i*= 1, 2, …, *n*. This assumption ensures that, on average, our observations align with the real line.
2. The assumption of homoscedasticity: The variance is denoted by σ^2 and remains constant across all values of the independent variables, i.e. Var (u_i)= σ^2 for every *i*= 1, 2, …, *n*. This assumption ensures that every observation holds equal reliability.
3. Assumptions of independence and no autocorrelation: The values of u_i are independent. The magnitude of the error for a specific set of independent variable values is unrelated to the magnitude of the error for any other set of values. *E* ($u_i u_j$)=0 for *i≠j*, *i*, *j* = 1, 2, …, *n*. This assumption ensures that the disturbances of the *i*-th observation do not convey any information about the disturbances of the *j*-th observation.
4. Assumptions of endogeneity and normality: The explanatory variable is non-stochastic and is uncorrelated with the error. The error (u_i) is a normally distributed random variable representing the discrepancy between the observed *Y* value and the expected *Y* value.

When any of the assumptions 1-3 is violated the corresponding OLS estimators are not blue anymore. However, if the the error terms (u_i) are not normally distributed but all the other conditions hold then the OLS estimators are still blue and proximate interferences are possible when the sample size is large enough (Baltagi, 2008).

The quality of fit for the estimated regression equation is represented by the coefficient of determination (R^2). This value signifies the extent of variability in *Y* that can be accounted for by the estimated regression equation (Spanos, 1986).

3.5.2 The simultaneous equation model

The simultaneous equations model provides a statistical methodology for solving and analyzing a system of interconnected equations within a theoretical framework (Spanos, 1986). When estimating the productivity equation (equation 6), it's crucial to acknowledge that variations in inputs are not independent of variations in outputs. Inputs and outputs are mutually determined by firms, implying that the variables on the right-hand side are correlated with the error term. This phenomenon is known as the endogeneity problem (Baltagi, 2008). In this context, the Ordinary Least Squares (OLS) technique yields biased estimates due to the correlation between explanatory variables and the error term. Such explanatory variables can be termed endogenous variables, which give rise to simultaneity issues during model estimation (Spiezia, 2013).

A method to address simultaneity problems is the use of instrumental variables or two-stage least squares (2SLS). In the first stage, the variables are estimated, and in the second stage, the endogenous variables enter the regression with their predicted values obtained from the first stage. These variables are then treated as exogenous and independent of the error term. They are related to the input but not directly to the output. This procedure allows for the identification of variations in the input that occur simultaneously with variations in the output(Spiezia, 2013).

To illustrate this procedure let us rewrite equation 7 in terms of Y_1 and X_1 as the output and input, respectively, and X_1 correlated with the error term u_1:

$$Y_1 = \alpha + \beta_1 X_1 + u_1 \qquad (15)$$

The endogenous explanatory variable (X_1) can be replaced by an exogenous one (W).

$$X_1 = \gamma + \beta_2 W + u_2 \qquad (16)$$

With $\hat{u}_2 = X_1 - \hat{X}_1$, satisfying the OLS normal equations $\sum_{i=1}^{n} \hat{u}_2 = \sum_{i=1}^{n} \hat{u}_2 W = 0$

The second-stage regression is conducted by substituting the value of X_1 in equation 15 with its estimated value $\hat{X}_1$. By utilizing equation 16, we can consequently rewrite equation 15 as follows:

$$Y_1 = \alpha + \beta_1 \hat{X}_1 + \varepsilon_1 \qquad (17)$$

With $\sum_{i=1}^{n} \hat{\varepsilon}_1 = \sum_{i=1}^{n} \hat{\varepsilon}_1 \hat{X}_1 = 0$

As a result, the error term ε_1 behaves similarly to the original disturbances u_1. However, the endogenous variable X_1 is represented by $\hat{X}_1$, which remains independent of the error term u_1 and is solely a linear function of the exogenous variable. Consequently, if all the exogenous variables within the system are incorporated in the initial step regression, the resulting estimator in the second stage is known as two-stage least squares (2SLS) (Baltagi, 2008).

The common approach of employing instrumental variables (IV) to address endogeneity and simultaneity challenges often encounters a common limitation – the search for appropriate IVs. The prevailing method involves the use of lagged values of the inputs. The quantity of lags employed can impact the eventual outcomes. However, another constraint arises when cross-sectional data is utilized, particularly in instances where information from the majority of companies surveyed is not replicated in prior surveys. This limitation restricts the scope of the research (Spiezia, 2013).

3.5.3 Generalized Linear Models

Another statistical tool that facilitates the derivation of mathematical equations to assess the association between innovation and productivity is the family if Generalized Linear Models (GLM) (Baum, 2016). GLMs framework is based on the so-called linear exponential family (LEF). Within this family, various distributions are encompassed, including Normal (Gaussian) and Inverse Gaussian for continuous data, Poisson and Negative Binomial for count data, Bernoulli for binary data (such as logit and probit), and Gamma for duration data (Baum, 2016).

The estimates of the model parameters in GLM are found by maximizing log-likelihood function given by:

$$Q(\theta) = \sum_{1}^{N}\left[a\big(m(x_i,\beta)\big) + b(y_i) + c\big(m(x_i,\beta)\big)\right] \qquad (18)$$

Here, represents the conditional mean of y, a(·) and c(·) correspond to different members of the LEF, and b(·) is a normalizing constant (Baum, 2016).

3.6 Data

For this research, cross-sectional data from the Innovation Survey 2021 with a reference period spanning from 2018 to 2020 was employed. The survey was jointly conducted in partnership with the Economy, Science, and Innovation Department at KU Leuven and the Flemish government. This innovation survey collected information regarding whether firms introduced new goods or services to the market, executed alterations in their internal procedures or organizational structure, or made investments to facilitate these changes.

The central aim of the survey is to leverage innovation statistics in order to align and benchmark economic policies for both firms and the country, within a dynamic competitive business environment. In the context of this study, a comprehensive confidential survey was administered to a total of 3554 firms, encompassing various economic activities. These activities included innovation-related, R&D, and ICT expenditures, alongside other dichotomous information that holds the potential to positively influence the evolution of innovative outcomes. To safeguard the privacy of information derived from statistical findings, each firm was assigned a distinct identifier.

The data was analyzed using descriptive statistics, and regression models were derived to elucidate the innovation process and its impact on firms' productivity.

3.7 Research methodology approach

The methodological approach for assessing the effects of innovation on productivity is based on adapted CDM and Cobb-Douglas production function models. This entails a two-step structural model, where the system equations are solved sequentially. In the initial step, innovation variations are correlated with their determinants, such as ICT and R&D investments. Subsequently, the expected values of innovation outputs from the preceding equations ($\widehat{In}_{out}^{i}$), serve as explanatory variables in the productivity equation. Labor productivity (PI) was quantified using a natural logarithmic transformation of the ratio between the average turnover reported in 2018 and 2020, and the labor input for both years. The capital stock (K) for the companies was not reported in the anonymized data.

The model equations are specified as follows:

$$In_{out}^{i} = \alpha_1 + \beta_{11}X_1 + \beta_{21}X_2 + \beta_{31}X_3 + \varepsilon_1 \quad (19)$$

$$lnPI = \alpha_2 + \beta_{12}\widehat{In}_{out}^{1} + \beta_{22}\widehat{In}_{out}^{2} + \beta_{32}\widehat{In}_{out}^{3} + \ldots\ldots + \varepsilon_2 \quad (20)$$

In case where the innovation outputs are measured as binary outcomes, the expected values for the response *Y* form a probability function ranging from 0 to 1. The Generalized Linear Model (GLM) then gives parameters that align with the link function for the dependent variable and its determinants (Baum, 2016).

During the empirical analysis, the regression outcomes of the Generalized Linear Models for equation 19 were assessed using the likelihood-ratio test to verify the significance of both the models and the parameter coefficients. For equation 20, a multiple linear regression model was employed with a backward selection method, and the coefficients were estimated using the Ordinary Least Squares (OLS) technique. The sample's descriptive statistics, modeling process, and results were derived using IBM SPSS Statistics version 28 software.

4 Research Results and Discussion

4.1 Data and summary statistics for the output variables

The research included an extensive dataset collected from 3,554 companies in Belgium. Table 1 showcases the diverse economic sectors to which these companies belong. Information concerning labor, turnover, as well as the development and enhancement of products and services was gathered for all companies. This included quantifying the intensity of these innovations, measured by the percentage of sales attributed to these new or improved offerings. This evaluation covered innovations that were novel to the company or even those that were already present in competitor offerings, along with products that had subtle modifications.

Regarding process innovation, the study collected data pertaining to the development or enhancement of process methods across various domains, including logistics, novel data processing and communication systems (ICT), administrative procedures, organizational enhancements, human resources, and marketing innovations. The majority of outcome data were binary in nature, with the exception of the percentage of sales attributed to innovations in products or services.

Table 1. Economic sectors analyzed in the study

No.	Sectors	No.	Sectors
1	Other mining and quarrying	**25**	Repair and installation of machinery and equipment
2	Manufacture of food products	**26**	Electricity, gas, steam and air conditioning supply
3	Manufacture of beverages	**27**	Water collection, treatment and supply
4	Manufacture of tobacco products	**28**	Sewerage
5	Manufacture of textiles	**29**	Waste collection, treatment and disposal activities; materials recovery
6	Manufacture of wearing apparel	**30**	Remediation activities and other waste management services
7	Manufacture of wood and of wood and cork	**31**	Wholesale trade, except of motor vehicles and motorcycles
8	Manufacture of paper and paper products	**32**	Retail trade, except of motor vehicles and motorcycles
9	Printing and reproduction of recorded media	**33**	Land transport and transport via pipelines
10	Manufacture of coke and refined petroleum products	**34**	Water transport
11	Manufacture of chemicals and chemical products	**35**	Warehousing and support activities for transportation
12	Manufacture of basic pharmaceutical products and pharmaceutical preparations	**36**	Postal and courier activities
14	Manufacture of rubber and plastic products	**37**	Publishing activities
15	Manufacture of other non-metallic mineral products	**38**	Motion picture, video and television programme production, sound recording and music publishing activities

16	Manufacture of basic metals	**39**	Programming and broadcasting activities
17	Manufacture of fabricated metal products, except machinery and equipment	**40**	Telecommunications
18	Manufacture of computer, electronic and optical products	**41**	Computer programming, consultancy and related activities
19	Manufacture of electrical equipment	**42**	Information service activities
20	Manufacture of machinery and equipment	**43**	Financial service activities, except insurance and pension funding
21	Manufacture of motor vehicles, trailers and semi-trailers	**44**	Insurance, reinsurance and pension funding, except compulsory social security
22	Manufacture of other transport equipment	**45**	Activities auxiliary to financial services and insurance activities
23	Manufacture of furniture	**46**	Architectural and engineering activities; technical testing and analysis
24	Other manufacturing	**47**	Scientific research and development

The descriptive statistics for product innovation intensity outputs were presented for the following variables in Table 2: Turnimp20 (percentage of sales from improved product innovation present in your offerings), Turmar (percentage of sales from new product innovation compared to your competitors' offerings), Turnin (percentage of sales from product innovation already present in your offerings, also offered by your competitors), and Turung (percentage of sales from other unchanged or slightly changed products).

These results allow us to assess that the majority of companies experience an increase in sales from products that already exist in their offerings but have been improved (Turnimp20), showing an average sales increase of approximately 7.6%. In contrast, for the remaining product innovations, the increase is less than 1%. It is important to note that, in the case of the variable Turnimp20, there is significantly higher variance, standard deviation, and range, with a maximum reported value of 100%. For the other variables, the maximum value is 1%.

Table 2. Descriptive statistics for product innovation intensity outputs

		Turnimp20	Turnmar	Turin	Turung
No.	Valid	3100	3345	3303	3228
	Missing	454	209	251	326
Mean		7.609	0.065	0.120	0.815
Std. Error of Mean		0.291	0.003	0.004	0.005
Std. Deviation		16.248	0.164	0.226	0.304
Variance		264.02	0.027	0.051	0.093
Range		100	1.00	1.00	1.00
Minimum		0.00	0.00	0.00	0.00
Maximum		100	1.00	1.00	1.00

The intensity output of various product innovation variables and the measure of productivity intensity (PI) were assessed using Pearson correlation, as shown in Table 3. The notable finding is that only the variable Turung (percentage of sales for products that remain unchanged or undergo only slight changes) demonstrates a positive Pearson correlation with PI. In contrast, the remaining product innovation variables exhibit a negative correlation with PI. However, the test did not yield statistical significance for the correlations among the studied variables.

Table 3. Pearson correlation between PI and product innovation outputs

			95 % confidence interval (2 tailed)	
	Pearson correlation	Sig. (2 tailed)	lower	upper
PI - Turnimp20	-0.025	0.187	-0.063	0.012
PI - Turnmar	-0.022	0.241	-0.058	0.015
PI - Turin	-0.021	0.266	-0.057	0.016
PI - Turung	0.026	0.164	-0.011	0.063

Process innovation was evaluated by recording various types of output as binary data in the survey. The reported process innovations were categorized as follows:

1. Inpsprd: This category pertains to new production procedures, such as increased automation or enhanced energy efficiency.
2. Inpslog: Refers to innovations in logistics, including improvements in supply chain operations, in-house processes, warehouse management, and operational resources.
3. Inpsict: Denotes new information processing or communication systems (ICT), indicating advancements in digital technologies for data handling and communication.
4. Inpsadmin: Relates to new accounting or administrative processes, such as the adoption of accounting software, novel invoice processing methods, or planning software.
5. Inpsorgrel: Represents innovations in process organization, encompassing areas like quality management, security policies, and front/back office support. It also includes the reorganization of external relations, such as partnerships or outsourcing.
6. Inpshrm: Pertains to new organizational structures and decision-making processes in human resources, such as the implementation of agile teams or the integration/deintegration of departments.
7. Inpsmkting: Focuses on the adoption of new marketing methods to promote products or services.

Each of these categories reflects a specific aspect of process innovation and contributes to an overall understanding of how companies are improving their operational processes.

The frequency statistics for each process innovation output are reported in Table 4. In this table, the number 1 represents a company reporting a specific type of process innovation, while 0 represents the absence of such a report. Taking into account the valid percentage, which calculates the reported frequency of process innovation while excluding missing values from the data, the most frequently reported process innovation is Inpscit (52.4%), which is related to new data processing and communication systems. It is followed by Inpsadmin, Inpsprd, and Inpsorgrel with values around 45.0%. The remaining reported process innovations (Inpsmkting, Inpshrm, and Inpslog) are each less than 30.0%. These results highlight the relevance for firms of introducing new data processing and communication systems, due to their interconnection with other departments and their impact on firm performance.

The Pearson correlation between the productivity intensity (PI) and the different types of process innovation was not conducted due to limitations in the test with binary or categorical variables.

Table 4. Frequency statistics for process innovation outputs

		Frequency	Percent	Valid Percent
Inpsprd	0	1932	54.4	54.6
	1	1604	45.1	45.4
	Total	3536	99.5	100
Inpslog	0	2618	73.7	74.1
	1	914	25.7	25.9
	Total	3532	99.4	100
Inpsict	0	1680	47.3	47.6
	1	1853	52.1	52.4
	Total	3533	99.4	100
Inpsadmin	0	1918	54.0	54.2
	1	1618	45.5	45.8
	Total	3536	99.5	100
Inpsorgrel	0	1961	55.2	55.5
	1	1573	44.3	44.5
	Total	3534	99.4	100
Inpshrm	0	2595	73.0	73.4
	1	939	26.4	26.6
	Total	3534	99.4	100
Inpsmkting	0	2477	69.7	70.2
	1	1054	29.7	29.8
	Total	3531	99.4	100

4.2 Data and summary statistics for the input variables

The input variables used in the research were divided into two groups: binary data with two categories (0 and 1), where 0 indicates a negative response and 1 indicates a positive response, and continuous variables. These variables enabled the measurement of investment and expenditure intensity across various areas, including information and communication technologies, research & development, and other subdivided expense categories.

4.2.1 Categorical variables and frequency statistics

The categorical variables measured during the innovation survey include:

1. Inpdself (self-developed product or service)

2. Inpswith (process innovation developed in collaboration)

3. Intrd (internal R&D)

4. Extrd (external R&D)

5. Rdbio (R&D in biotechnology or biochemistry sectors)

6. Rdnano (R&D in nanotechnology sector)

7. Rdai (R&D in artificial intelligence sector)

8. Cord (R&D in coordination with other entities)

The variable Inpdself was exclusively utilized for the product innovation models, whereas Inpswith was introduced as an explanatory variable in the models developed for process innovation. The remaining categorical variables were employed as explanatory variables in both types of model for innovation outputs.

Table 5 presents the frequency statistics for these variables. Based on the analysis, it is observed that 41.4% of companies engaged in self-developed product/service innovations, while 58.6% pursued collaborative efforts with other entities. In the context of process innovation, approximately 40.0% of companies opted for collaboration to achieve their goals.

A significant majority of the entities, almost 60.0%, chose to conduct internal R&D studies. Conversely, fewer than 30.0% of companies outsourced their R&D studies. In terms of the sectors where R&D is carried out, artificial intelligence reported the highest percentage at 13.8%. This value surpasses the combined total of R&D studies reported in the biotechnology or biochemistry and nanotechnology sectors. This trend might be attributed to the growing advantages of artificial intelligence in automating research processes, encompassing data collection, analysis, interpretation, pattern identification, and the creation of tailored business solutions (Enholm et al., 2022). Furthermore, evidence supports the notion that investing in artificial intelligence leads to increased firm revenues, and the benefits of such adoption are amplified when combined with complementary technologies and an internal R&D strategy (Lee et al., 2022).

Considering R&D collaboration among entities, only 31% of companies reported engaging in such collaborations.

Table 5. Frequency statistics for the categorical input variables

		Frequency	Percent	Valid Percent
Inpdself	0	2070	58.2	58.6
	1	1465	41.2	41.4
	Total	3535	99.5	100
Inpswith	0	2106	59.3	60.4
	1	1404	39.5	40.0
	Total	3510	98.8	100
Intrd	0	1461	41.1	42.8
	1	1956	55.0	57.2

	Total	3417	96.1	100
Extrd	0	2353	66.2	78.7
	1	638	18.0	21.3
	Total	2991	84.2	100
Rdbio	0	3105	87.4	93.4
	1	220	6.2	6.6
	Total	3325	93.6	100
Rdnano	0	3239	91.1	97.4
	1	85	2.4	2.6
	Total	3324	93.5	100
Rdai	0	2860	80.5	86.2
	1	458	12.9	13.8
	Total	3318	93.4	100
Cord	0	2255	63.4	69.0
	1	1015	28.6	31.0
	Total	3270	92.0	100

4.2.2 Continuous variables and their corresponding descriptive statistics

The research employed a set of continuous variables to assess the relationship between innovation and productivity. These variables include:

1. Invinno20: Investment in innovation for the acquisition of machinery, equipment, software, or buildings.
2. Invpatent20: Acquisition of existing know-how, intellectual property (IP), or non-patented inventions for innovations.
3. Invmarket20: Expenditures on market research or advertising during the launch of innovations.
4. Invoth20: Other expenses related to innovations, such as feasibility studies, testing, routine software development, design, and training.
5. Totrd20: Total Research and Development (R&D) expenses, encompassing gross wage costs of R&D employees, expenditures on external consultants who conducted R&D under the company’s direct supervision, outsourced/purchased R&D, and investments specifically allocated to R&D facilities, machinery, software, and new intellectual property.

Indeed, several of these variables (Invinno20, Invoth20, and Totrd20) enclose investments, either directly or indirectly, in Information and Communication Technology (ICT). This includes allocations towards software, hardware, and infrastructure that contribute to the development of innovation and R&D efforts. This recognition of ICT's significance stems from its pivotal role in enhancing a firm's innovative capacity and productivity (Najafi-Tavani et al., 2018).

Table 6 presents the descriptive statistics for these variables, which serve as inputs in the developed models. The results evidence a significant degree of variability among the investments made. Examining the mean values, the most substantial investments are allocated to total Research and

Development (R&D) expenses (Totrd20), followed by investments in machinery, equipment, software, or buildings (Invinno20), and other expenses related to innovations (Invoth20).

Table 6. Descriptive statistics for the continuous input variables

	Invinno20	Invpatent20	Invmarket20	Invoth20	Totrd20
N statistics	3243	3037	3051	3074	2990
Mean	5.0002E+005	3.0531E+004	2.3579E+004	8.5417E+004	2.3233E+006
Std. Error of Mean	8.00925E+004	1.47375E+004	9.91050E+003	1.12534E+004	7.92240+E005
Std. Deviation	4.56106+E006	8.12166+E005	5.47415+E005	6.23932E+005	4.33204E+007
Variance	2.080E+13	6.596E+11	2.997E+11	3.893E+11	1.877E+15
Range	1.59E+008	4.14E+007	2.94E+007	1.94E+007	2.21E+009
Minimum	0.00E+000	0.00E+000	0.00E+000	0.00E+000	0.00E+000
Maximum	1.59E+008	4.14E+007	2.94E+007	1.94E+007	2.21E+009

4.3 Models for the output response of product innovation

Product innovation models (Tables 7 to 10) were established to analyze the correlations between the four measured product innovation outputs (Turnimp20, Turnmar, Turin, and Turung) and various types of investments, including R&D, ICT, patents, market studies, internal or external R&D, R&D sectors, and collaborative R&D efforts. These models were developed using the Generalized Linear Models (GLM) methodology, as detailed in the Research methodology explained in sections 3.5.3 and 3.7.

Four linear models were formulated, using a normal distribution function with an identity link. The parameters were extimated using the maximum likelihood procedure, and their significance was assessed using the likelihood-ratio test. This technique evaluates the goodness of fit between competing statistical models(Spanos, 1986). The goodness of fit the GLMs was informally evaluated based on the deviance (provided below each table), which is calculated as -2 times the difference in log-likelihood between the current model and a model that achieves a perfect fit with the data (*Deviance*, n.d.).

Table 7. Model for the innovation output of Turnimp20 (percentage of sales from improved product innovation in your product offering)

Parameters	B	Std. Error	95 % Confidence Interval		likelihood-ratio test[b] (type III)	Sig.
Intercept	18.121	2.475	13.267	22.975	57.72	<0.001
Inpdself[a]	-15.295	0.797	-16.858	-13.733	338.82	0.000
Intrd[a]	-1.367	0.848	-3.03	0.297	2.59	0.107
Exrd[a]	0.015	0.971	-1.889	1.920	0.000	0.987
Rdbio[a]	3.487	1.574	0.400	6.574	4.90	0.027

Rdnano[a]	0.625	2.204	-3.697	4.947	0.080	0.777
Rdai[a]	-5.041	1.092	-7.182	-2.900	21.21	<0.001
Cord[a]	0.385	0.967	-1.512	2.282	0.159	0.690
Invinno20	-5.648E-8	1.087E-7	-2.697E-7	1.567E-7	0.270	0.630
Invpatent20	-4.457E-7	1.713E-6	-3.805E-6	2.914E-6	0.068	0.795
Invmarket20	-1.0316E-6	1.443E-6	-4.145E-6	1.513E-6	0.832	0.362
Invoth20	4.733E-7	7.291E-7	-9.564E-7	1.903E-6	0.421	0.516
Totrd20	3.985E-8	5.535E-8	-6.869E-8	1.484E-7	0.518	0.472

a. categorical variables and the parameters is when this is taken into account or equal 0 otherwise

b. df equal 1

the scaled deviance for the model is 2053 and df 2040

Table 8. Model for the innovation output of Turnmar (percentage of sales from new product innovation in relation to your competitors' offerings)

Parameters	B	Std. Error	95 % Confidence Interval		likelihood-ratio test[b] (type III)	Sig.
Intercept	0.258	0.026	0.206	0.310	93.49	0.000
Inpdself[a]	-0.084	0.008	-0.100	-0.069	108.58	0.000
Intrd[a]	-0.060	0.009	-0.077	-0.043	45.89	<0.001
Exrd[a]	0.021	0.010	0.001	0.041	4.16	0.041
Rdbio[a]	0.001	0.016	-0.03	0.032	0.004	0.950
Rdnano[a]	-0.109	0.024	-0.156	-0.063	21.16	<0.001
Rdai[a]	-0.027	0.011	-0.050	-0.005	5.70	0.017
Cord[a]	0.002	0.010	-0.018	0.021	0.026	0.872
Invinno20	-5.275E-10	1.168E-9	-2.817E-9	1.762E-9	0.204	0.651
Invpatent20	2.213E-8	1.847E-8	-1.409E-8	5.834E-8	1.44	0.231
Invmarket20	2.788E-8	1.555E-8	-2.607E-9	5.837E-8	3.21	0.073
Invoth20	-6.384E-10	7.885E-9	-1.610E-8	1.482E-8	0.007	0.935
Totrd20	-1.188E-9	5.964E-10	-2.358E-9	-1.862E-11	3.97	0.046

a. categorical variables and the parameters is when this is taken into account or equal 0 otherwise

b. df equal 1

the scaled deviance for the model is 2159 and df 2146

Table 9. Model for the innovation output of Turnin (percentage of sales from product innovation already offered by your competitors but present in your product offering)

Parameters	B	Std. Error	95 % Confidence Interval		likelihood-ratio test[b] (type III)	Sig.
Intercept	0.300	0.038	0.224	0.375	69.29	<0.001
Inpdself[a]	-0.218	0.011	-0.239	-0.196	350.32	0.000
Intrd[a]	0.007	0.012	-0.017	0.031	0.331	0.565
Exrd[a]	-0.017	0.014	-0.045	0.011	1.38	0.239
Rdbio[a]	0.041	0.022	-0.003	0.085	3.37	0.066
Rdnano[a]	-0.019	0.034	-0.085	0.047	0.320	0.572
Rdai[a]	-0.049	0.016	-0.081	-0.018	9.52	0.002
Cord[a]	-0.021	0.0141	-0.049	0.007	2.23	0.135

Invinno20	4.774E-10	1.599E-9	-2.658E-9	3.613E-9	0.089	0.765
Invpatent20	8.387E-9	2.544E-8	-4.151E-8	5.828E-8	0.109	0.742
Invmarket20	1.053E-8	2.133E-8	-3.129E-8	5.236E-8	0.244	0.621
Invoth20	5.126E-9	1.040E-8	-1.526E-8	2.551E-8	0.243	0.622
Totrd20	-5.169E-10	8.162E-10	-2.117E-9	1.084E-9	0.401	0.527

a. categorical variables and the parameters is when this is taken into account or equal 0 otherwise

b. df equal 1

the scaled deviance for the model is 2137 and df 2124

Table 10. Model for the innovation output of Turung (percentage of sales for other, unchanged, or slightly changed products)

Parameters	B	Std. Error	95 % Confidence Interval		likelihood-ratio test[b] (type III)	Sig.
Intercept	0.403	0.047	0.310	0.496	704.74	0.000
Inpdself[a]	0.315	0.014	0.288	0.342	463.79	0.000
Intrd[a]	0.051	0.015	0.021	0.081	11.37	<0.001
Exrd[a]	-0.006	0.018	-0.041	0.029	0.106	0.745
Rdbio[a]	-0.026	0.278	-0.080	0.029	0.848	0.357
Rdnano[a]	0.144	0.041	0.063	0.225	12.11	<0.001
Rdai[a]	0.079	0.020	0.040	0.117	15.83	<0.001
Cord[a]	0.014	0.017	-0.020	0.048	0.640	0.424
Invinno20	5.110E-10	1.978E-9	-3.368E-9	4.390E-9	0.067	0.796
Invpatent20	-2.610E-8	3.121E-8	-8.730E-8	3.510E-8	0.699	0.403
Invmarket20	-3.415E-8	2.629E-8	-8.571E-8	1.741E-8	1.686	0.194
Invoth20	-8.626E-9	1.334E-8	-3.478E-8	1.753E-8	0.418	0.518
Totrd20	1.560E-9	1.009E-9	-4.187E-10	3.538E-9	2.388	0.122

a. categorical variables and the parameters is when this is taken into account or equal 0 otherwise

b. df equal 1

the scaled deviance for the model is 2107 and df 2094

According to the findings, only self-developed products or services (Inpdself) exhibit a statistically significant effect at a 5% significance level across all four types of product innovation studied. However, this impact is positive solely for the sales percentage of other, unchanged, or slightly changed products (Turung). Among these variables, Turung experiences a positive influence from all significant independent variables, with the most pronounced impact originating from Inpdself (0.315), followed by Rdnano (0.144), Rdai (0.079), and Intrd (0.051).

The outcomes reveal a non-uniform effect of explanatory variables on various types of product innovation outputs. In general, variables encompassing measures of Information and Communication Technology (ICT) (such as Invinno20, Invoth20, and Totrd20), along with investments linked to intellectual property, know-how, and patents (Invpatent20), or market research during innovation launches (Invmarket20), lack a significant impact on the developed models. Notably, Invoth20 for Turmar demonstrates a significance, albeit with a negative coefficient or elasticity.

While the impact of ICT investments (measured through Invinno20, Invoth20, and Totrd20) on most product innovation outputs couldn't be confirmed at the 5% significance level, the results do suggest positive coefficients or elasticities for certain cases. Specifically, Invoth20 and Totrd20 exhibit favorable tendencies with Turimp20, Invinno20, and Invoth20 with Turin, and Invinno20 and Totrd20 with Turung. This implies a potentially beneficial relationship between these types of investments and product innovation outputs.

4.4 Models for the output response of process innovation

The parameters and their significance for the process innovation models, developed to elucidate how the input variables (continuous and categorical variables selected in sections 4.2.1 and 4.2.2) influence the possibility of creating various types of innovation—Inpsprd (new process method innovation), Inpslog (new process logistic innovation), Inpsict (new data process and communication system innovation), Inpsadmin (new administrative system innovation), Inpsorgrel (new organizational innovation), Inpshrm (new human resources innovation), and Inpsmkting (new marketing innovation)—are presented in Tables 11 to 18. These models were also based on Generalized Linear Models (GLM) and the Research Methodology proposed in sections 3.5.3 and 3.7. In these cases, since the responses consist of binary or categorical data, a Binomial probability distribution with a logit link function was used. The parameters were gain estimated using the maximum likelihood procedure and the signficance of the effects was determined using the likelihood ratio tests.

Table 11. Innovation output model for Inpsprd (new process method innovation)

Parameters	B	Std. Error	95 % Confidence Interval		likelihood-ratio test[b] (type III)	Sig.
Intercept	-1.768	0.299	-2.377	-1.199	0.467	0.494
Intrd[a]	1.406	0.079	1.252	1.561	316.61	0.000
Exrd[a]	-0.001	0.104	-0.205	0.204	0.000	0.996
Rdbio[a]	0.154	0.164	-0.163	0.479	0.897	0.344
Rdnano[a]	0.547	0.270	0.036	1.100	4.42	0.036
Rdai[a]	0.188	0.114	-0.034	0.413	2.76	0.096
Cord[a]	0.091	0.100	-0.105	0.287	0.831	0.362
Inpswith[a]	0.947	0.063	0.823	1.070	221.47	0.000
Invinno20	-5.906E-7	8.071E-8	-7.590E-7	-4.426E-7	111.01	0.000
Invpatent20	-1.014E-8	3.953E-7	-6.149E-7	8.821E-7	0.001	0.980
Invmarket20	-6.462E-8	2.297E-7	-8.598E-7[c]	4.880E-7	0.073	0.787
Invoth20	1.195E-7	1.022E-7	-6.462E-8	3.438E-7	1.60	0.206
Totrd20	2.165E-8	8.723E-9	[d]	4.169E-8	8.49	0.004

a. categorical variables and the parameters is when this is taken into account or equal 0 otherwise

b. df equal 1

the scaled deviance for the model is 4732 and df 1363

c. The validity of the confidence limit is uncertain because the maximum number of profile likelihood confidence interval iterations was reached but convergence was not achieved. Results are based on the last iteration.

d. Unable to compute because some convergence criteria were not satisfied.

Table 12. Innovation output model for Inpslog (new process logistic innovation)

Parameters	B	Std. Error	95 % Confidence Interval		likelihood-ratio test[b] (type III)	Sig.
Intercept	-0.193	0.257	-0.694	0.315	47.29	<0.001
Intrd[a]	0.356	0.088	0.183	0.527	16.13	<0.001
Exrd[a]	0.286	0.103	0.083	0.489	7.62	0.006
Rdbio[a]	0.258	0.154	-0.046	0.559	2.78	0.096
Rdnano[a]	0.356	0.231	-0.102	0.806	2.33	0.126
Rdai[a]	-0.316	0.119	-0.550	-0.085	7.20	0.007
Cord[a]	-0.198	0.104	-0.402	0.004	3.68	0.055
Inpswith[a]	1.429	0.067	1.297	1.561	456.73	0.000
Invinno20	-3.421E-8	1.413E-8	-6.412E-8	-8.454E-9	7.08	0.008
Invpatent20	-1.350E-7	1.855E-7	-5.530E-7	2.342E-7	0.537	0.464
Invmarket20	-2.264E-7	1.912E-7	-7.161E-7	3.806E-7[c]	1.77	0.183
Invoth20	4.740E-8	8.238E-8	-1.061E-7	2.338E-7	0.352	0.553
Totrd20	4.638E-9	6.366E-9	-8.522E-9	1.726E-8	0.509	0.476

a. categorical variables and the parameters is when this is taken into account or equal 0 otherwise

b. df equal 1

the scaled deviance for the model is 4191 and df 1363

c. The validity of the confidence limit is uncertain because the maximum number of profile likelihood confidence interval iterations was reached but convergence was not achieved. Results are based on the last iteration.

Table 13. Innovation output model for Inpsict (new data process and communication system innovation)

Parameters	B	Std. Error	95 % Confidence Interval		likelihood-ratio test[b] (type III)	Sig.
Intercept	-1.731	0.307	-2.343	-1.140	2.92	0.087
Intrd[a]	0.962	0.082	0.801	1.122	137.53	0.000
Exrd[a]	-0.063	0.114	-0.286	0.160	0.308	0.579
Rdbio[a]	-0.068	0.173	-0.403	0.275	0.155	0.694
Rdnano[a]	-0.499	0.264	-1.009	0.028	3.45	0.063
Rdai[a]	1.014	0.138	0.747	1.290	58.88	<0.001
Cord[a]	-0.073	0.110	-0.287	0.142	0.440	0.507
Inpswith[a]	1.670	0.064	1.545	1.797	720.28	0.000
Invinno20	2.884E-8	1.519E-8	-1.586E-9	5.902E-8	3.46	0.063
Invpatent20	-6.580E-6	2.244E-6	-1.132E-5	-2.552E-6	13.11	<0.001
Invmarket20	-6.606E-6	1.931E-6	-1.069E-5	-3.185E-6	21.95	<0.001
Invoth20	-2.619E-7	1.578E-7	-6.146E-7	7.521E-9	3.59	0.058
Totrd20	-3.517E-9	1.060E-8	-2.757E-8	1.496E-8	0.116	0.734

a. categorical variables and the parameters is when this is taken into account or equal 0 otherwise

b. df equal 1

the scaled deviance for the model is 4311 and df 1363

Table 14. Innovation output model for Inpsadmin (new administrative system innovation)

Parameters	B	Std. Error	95 % Confidence Interval		likelihood-ratio test[b] (type III)	Sig.
Intercept	-1.299	0.271	-1.837	-0.774	0.013	0.908
Intrd[a]	0.771	0.080	0.615	0.927	93.18	0.000
Exrd[a]	0.039	0.103	-0.164	0.242	0.139	0.709
Rdbio[a]	-0.166	0.157	-0.472	0.143	1.11	0.292
Rdnano[a]	0.129	0.243	-0.342	0.612	0.285	0.593
Rdai[a]	0.562	0.115	0.338	0.789	24.34	<0.001
Cord[a]	-0.405	0.101	-0.604	-0.207	16.07	<0.001
Inpswith[a]	1.636	0.062	1.515	1.758	736.96	0.000
Invinno20	1.908E-8	1.277E-8	-4.579E-9	4.695E-8	2.464	0.116
Invpatent20	-5.313E-7	3.682E-7	-1.609E-6	-5.311E-8	4.99	0.026
Invmarket20	-3.890E-7	1.778E-7	-8.040E-7	-6.176E-8	5.51	0.019
Invoth20	6.565E-9	7.663E-8	-1.585E-7	1.593E-7	0.007	0.932
Totrd20	1.353E-8	6.553E-9	1.047E-9	2.727E-8	4.52	0.034

a. categorical variables and the parameters is when this is taken into account or equal 0 otherwise

b. df equal 1

the scaled deviance for the model is 4090 and df 1363

Table 15. Innovation output model for Inpsorgrel (new organizational innovation)

Parameters	B	Std. Error	95 % Confidence Interval		likelihood-ratio test[b] (type III)	Sig.
Intercept	-1.351	0.274	-1.897	-0.819	1.91	0.167
Intrd[a]	1.209	0.080	1.052	1.366	223.29	0.000
Exrd[a]	-0.140	0.104	-0.345	0.063	1.826	0.177
Rdbio[a]	0.109	0.158	-0.199	0.423	0.479	0.489
Rdnano[a]	-0.241	0.240	-0.709	0.236	0.996	0.318
Rdai[a]	0.634	0.117	0.405	0.866	30.14	<0.001
Cord[a]	0.167	0.100	-0.030	0.363	2.77	0.096
Inpswith[a]	1.351	0.063	1.228	1.475	460.43	0.000
Invinno20	2.228E-8	1.472E-8	-7.953E-9	5.134E-8	2.15	0.142
Invpatent20	-6.059E-7	5.903E-7	-2.092E-6	1.895E-7	1.71	0.191
Invmarket20	-4.347E-7	4.137E-7	-1.531E-6	[c]	1.84	0.175
Invoth20	-3.500E-7	1.616E-7	-6.988E-7	-7.075E-8	6.71	0.010
Totrd20	1.788E-10	8.323E-9	-1.797E-8	1.545E-8	0.000	0.983

a. categorical variables and the parameters is when this is taken into account or equal 0 otherwise

b. df equal 1

the scaled deviance for the model is 4233 and df 1363

c. Unable to compute because some convergence criteria were not satisfied.

Table 16. Innovation output model for Inpshrm (new human resources innovation)

Parameters	B	Std. Error	95 % Confidence Interval		likelihood-ratio test[b] (type III)	Sig.
Intercept	0.347	0.281	-0.195	0.907	103.21	0.000
Intrd[a]	0.784	0.093	0.601	0.965	68.32	<0.001
Exrd[a]	0.102	0.105	-0.105	0.307	0.931	0.335
Rdbio[a]	-0.529	0.167	-0.862	-0.206	10.47	0.001
Rdnano[a]	-0.597	0.252	-1.103	-0.113	5.88	0.015
Rdai[a]	0.951	0.112	0.733	1.171	73.13	0.000
Cord[a]	0.233	0.102	0.033	0.434	5.19	0.023
Inpswith[a]	1.177	0.073	1.035	1.320	260.20	0.000
Invinno20	1.166E-8	1.226E-8	-1.131E-8	3.829E-8	0.962	0.327
Invpatent20	-2.420E-8	2.057E-7	-4.490E-7	4.011E-7	0.014	0.906
Invmarket20	-7.680E-6	1.311E-6	-1.041E-5	-5.276E-6	68.24	<0.001
Invoth20	-6.056E-8	8.572E-8	-2.536E-7	1.028E-7	0.531	0.466
Totrd20	-9.432E-10	7.468E-9	-1.615E-8	1.380E-8	0.016	0.899

a. categorical variables and the parameters is when this is taken into account or equal 0 otherwise

b. df equal 1

the scaled deviance for the model is 3913 and df 1363

Table 17. Innovation output model for Inpsmkting (new marketing innovation)

Parameters	B	Std. Error	95 % Confidence Interval		likelihood-ratio test[b] (type III)	Sig.
Intercept	-1.354	0.274	-1.897	-0.824	6.73	0.010
Intrd[a]	0.658	0.086	0.489	0.826	56.40	<0.001
Exrd[a]	0.255	0.102	0.057	0.455	6.29	0.012
Rdbio[a]	-0.196	0.156	-0.503	0.108	1.60	0.206
Rdnano[a]	0.732	0.241	0.264	1.210	9.47	0.002
Rdai[a]	0.696	0.111	0.478	0.914	39.38	<0.001
Cord[a]	-0.075	0.100	-0.272	0.121	0.565	0.452
Inpswith[a]	1.366	0.067	1.235	1.496	421.49	0.000
Invinno20	5.220E-8	1.824E-8	2.010E-8	9.190E-8	11.69	<0.001
Invpatent20	-1.183E-7	3.194E-7	-6.563E-7	5.465E-7	0.131	0.717
Invmarket20	-1.910E-6	7.307E-7	-3.44E-6	-6.059E-7	19.04	<0.001
Invoth20	-3.964E-7	1.382E-7	-6.838E-7	-1.428E-7	10.90	<0.001
Totrd20	1.919E-8	8.823E-9	3.155E-9	3.828E-8	5.61	0.018

a. categorical variables and the parameters is when this is taken into account or equal 0 otherwise

b. df equal 1

the scaled deviance for the model is 4308 and df 1363

The results from Tables 11 to 17 reveal the parameters of the explanatory variables and their effects at a 5% significance level on different types of process innovation output models. According to the findings, the explanatory variables that exhibit significant effects across all types of process innovation outputs are internal R&D activities (Intrd) and collaborative processes for developing process innovations (Inpswith). Regarding their coefficients or elasticities, it is possible to discern some consistent effects: these variables have a positive impact on the output response, with coefficient values ranging between 0.356 and 1.636. However, no consistent effects were found for the remaining significant explanatory variables.

The results corroborate that R&D activities, alongside effective collaboration, play an indispensable role in driving a firm's process innovation. These activities promote a coaction of expertise and insights, leading to a deeper understanding of existing processes and their potential for improvement. Furthermore, collaborative processes encourage brainstorming and the generation of new ideas. R&D teams have often specialized technical skills, and by building collaborations, these skills can be joined to tackle firm challenges, thereby generating new solutions that enhance process efficiency. Wang & Wang (2012), have also discussed upon the symbiotic interplay of collaboration, innovation, and firm performance. Their study highlights the profound impact of explicit and strategic knowledge sharing on the quality of innovation, which in turn translates into enhanced operational efficiency and superior financial performance.

Compared to the developed models for product innovations, it is evident that at least one of the explanatory variables (Invinno20, Invoth20, and Totrd20), which measure ICT investments, exhibits significant effects on five process innovation models (Inpsprd, Inpslog, Inpsorgrel, Inpsadmin, and Inpsmkting). Additionally, at least one of the explanatory variables that measure investments related to intellectual property, know-how, and patents (Invpatent20) or market research during innovation launches (Invmarket20) demonstrates significant effects on four process innovation models (Inpsict, Inpsadmin, Inpshrm, and Inpsmkting).

The explanatory variable Totrd20 exhibits a significant positive elasticity in the Inpsprd, Inpsadmin, and Inpsmkting innovation models, while Invinno20 shows a positively significant effect in the Inpsmkting model.

However, even when it wasn't possible to establish the effect of explanatory variables measuring ICT investments (Invinno20, Invoth20, and Totrd20) at a 5% significance level in certain process innovation models, positive coefficients or elasticities were observed. Specifically, the explanatory variable Invinno20 demonstrated positive coefficients in the Inpsict, Inpsadmin, Inpsorgrel, and Inpshrm models; Invoth20 exhibited positive coefficients in the Inpsprd, Inpslog, and Inpsadmin models; and Totrd20 showed positive coefficients in the Inpslog and Inpsorgrel models.

These findings suggest a favorable impact of ICT investments on promoting process innovation outputs. ICT investments can drive process innovations by enhancing efficiency, enabling data-driven insights, facilitating collaborative activities, and providing access to information and customization (Kretschmer, 2012).

4.5 Effect of innovation outputs on productivity

The evaluation of the various forms of innovation output on productivity intensity (PI) was conducted using the linear regression model (equation 20) explained in section 3.7. This was accomplished through the implementation of a backward stepwise methodology. The backward stepwise methodology is a variable selection technique utilized in multiple linear regression to identify the most relevant set of explanatory variables for predicting a dependent variable or response. The approach starts with a model containing all explanatory variables and then proceeds to iteratively eliminate the least significant variable, continuing until a final criterion is met, often a pre-defined p-value or significance threshold (Whitaker, 1997).

Table 18 presents the outcomes of the multiple linear regression process. In this process, all expected values of innovation outputs were initially considered as explanatory variables. Subsequently, the variable with the lowest p-value or significance was removed from the model, and this process was repeated until all final explanatory variables were found to be significant for the model at a 5% significance level. This iterative process resulted in the creation of a reduced model that best explains the effect of innovation on the productivity intensity equation (model 6). The R-square and adjusted R-square values remained consistently stable across models 1 through 6, and values around 0.07 and 0.066, respectively. Table 18 provides the parameters for each innovation output variable in the productivity intensity equation, along with their significance in each model.

The model that best describes productivity intensity comprises six innovation outputs: Turmar, Turin, Turung, Inpsprd, Inpsadmin, and Inpshrm. Equation 20 can be rewritten accordingly:

$$lnPI = -8.481 + 15.230\hat{T}_{urmar} + 10.858\hat{T}_{urin} + 11.311\hat{T}_{urung} + 0.862\hat{I}_{npsprd} - 0.798\hat{I}_{npsadmin} + 1.156\hat{I}_{npshrm} \quad (21)$$

Based on the exploratory results of this research, the firm productivity intensity (PI) is primarily positively influenced by product innovation outputs related to increased sales from innovative products that are new in comparison to competitors (Turmar). An increase of one unit in Turmar results in a 15.230 lnPI increment, with the other model parameters held constant. Similarly, sales from innovative products already present in your offerings but also offered by competitors (Turin), and sales from other mostly unchanged or slightly changed products (Turung) show comparable effects, with increments of 10.858 lnPI and 11.311 lnPI, respectively.

Other types of innovation outputs that significantly affect PI (at a 5% significance level) include process innovations related to new methods or production procedures (Inpsprd), new accounting or administrative processes (Inpsadmin), and new organizational or decision-making approaches in human resources (Inpshrm). However, their coefficients or elasticities are below 1.2 units.

The outcome of innovation on productivity is explained through a structural equation model (equations 19-20). Initially, explanatory variables were used to evaluate their impact on innovation outputs. Subsequently, the expected values of innovation outputs were employed as explanatory variables in the productivity equation. This approach enables us to infer the effect of the ICT component, measured within variables Invinno20, Invoth20, and Totrd20, on productivity.

Invinno20, Invoth20, and Totrd20 exhibit no significant effects on product innovations, except for the Totrd20 explanatory variable, which displays a negative input elasticity for Turmar output. However, at least one of these variables demonstrates a significant effect in Inpsprd, Inpslog, Inpsadmin, Inpsorgrel, or Inpsmkting process innovation models. Among these five process innovation models, only two (Inpsprd and Inpshrm) exhibit positive significant effects in the final productivity equation (equation 21).

It is important to emphasize the exploratory nature of this research. The R-squared value for equation 21 explains approximately 7% of the variability in the response. Unmeasured latent variables, along with endogeneity and simultaneity issues, may impact the outcomes. Furthermore, it's worth noting that the research could not isolate the ICT component or subdivide it into hardware and software variables due to constraints posed by the nature of the data and the innovation survey used.

Table 18. Parameters of the productivity equation model

	Parameters	Unstandardized B	Std. Error	t	Sig.	95% Confidence Interval for B	
Model 1	Intercept	-7.944	3.899	-2.038	0.042	-15.590	-0.298
	Turnimp20	-0.026	0.024	-1.084	0.279	-0.073	0.021
	Turnmar	14.668	4.353	3.369	<0.001	6.130	23.205
	Turin	11.908	3.480	3.422	<0.001	5.083	18.732
	Turung	10.628	3.948	2.692	0.007	2.885	18.371
	Inpsprd	0.815	0.214	3.805	<0.001	0.395	1.235
	Inpslog	0.232	0.486	0.476	0.634	-0.722	1.186
	Inpsict	-0.248	0.389	-0.639	0.523	-1.011	0.514
	Inpsadmin	-0.938	0.549	-1.709	0.088	-2.014	0.138
	Inpsorgrel	0.251	0.379	0.662	0.508	-0.493	0.995
	Inpshrm	1.168	0.361	3.237	0.001	0.460	1.876
	Inpsmkting	0.042	0.525	0.080	0.936	-0.988	1.073
Model 2	Intercept	-8.115	3.271	-2.481	0.013	-14.529	-1.700
	Turimp20	-0.025	0.019	-1.292	0.197	-0.062	0.013
	Turnmar	14.838	3.801	3.904	<0.001	7.384	22.292
	Turin	12.015	3.211	3.742	<0.001	5.718	18.312
	Turung	10.804	3.280	3.294	0.001	4.372	17.237
	Inpsprd	0.814	0.214	3.808	<0.001	0.395	1.233
	Inpslog	0.220	0.462	0.475	0.635	-0.687	1.126
	Inpsict	-0.260	0.360	-0.724	0.469	-0.966	0.445
	Inpsadmin	-0.906	0.378	-2.394	0.017	-1.648	-0.164
	Inpsorgrel	0.261	0.358	0.729	0.466	-0.441	0.963
	Inpshrm	1.189	0.249	4.784	<0.001	0.702	1.677
Model 3	Intercept	-8.750	2.984	-2.933	0.003	-14.602	-2.899
	Turnimp20	-0.018	0.013	-1.387	0.166	-0.044	0.007
	Turnmar	15.800	3.215	4.914	<0.001	9.495	22.106
	Turin	12.215	3.182	3.838	<0.001	5.974	18.457
	Turung	11.515	2.918	3.947	<0.001	5.793	17.238
	Inpsprd	0.862	0.188	4.596	<0.001	0.494	1.230
	Inpsict	-0.267	0.359	-0.743	0.458	-0.972	0.438
	Inpsadmin	-0.770	0.248	-3.106	0.002	-1.257	-0.284
	Inpsorgrel	0.285	0.354	0.805	0.421	-0.409	0.980
	Inpshrm	1.148	0.233	4.925	<0.001	0.691	1.606
Model 4	Intercept	-8.314	2.925	-2.842	0.005	-14.049	-2.578
	Turimp20	-0.017	0.013	-1.307	0.191	-0.042	0.008
	Turmar	15.340	3.155	4.863	<0.001	9.154	21.527

	Turin	11.792	3.131	3.766	<0.001	5.652	17.933
	Turung	11.142	2.874	3.877	<0.001	5.506	16.779
	Inpsprd	0.857	0.187	4.572	<0.001	0.489	1.225
	Inpsadmin	-0.885	0.194	-4.572	<0.001	-1.265	-0.506
	Inpsorgrel	0.156	0.308	0.505	0.614	-0.449	0.760
	Inpshrm	1.083	0.216	5.013	<0.001	0.659	1.507
Model 5	Intercept	-8.626	2.857	-3.020	0.003	-14.231	-3.026
	Turimp20	-0.018	0.013	-1.360	0.174	-0.043	0.008
	Turmar	15.618	3.106	5.029	<0.001	9.527	21.709
	Turin	12.141	3.053	3.976	<0.001	6.152	18.129
	Turung	11.438	2.813	4.066	<0.001	5.921	16.955
	Inpsprd	0.913	0.151	6.050	<0.001	0.617	1.209
	Inpsadmin	-0.830	0.159	-5.214	<0.001	-1.142	-0.518
	Inpshrm	1.149	0.173	6.632	<0.001	0.809	1.488
Model 6	Intercept	-8.481	2.855	-2.970	0.003	-14.081	-2.881
	Turmar	15.230	3.093	4.924	<0.001	9.164	21.297
	Turin	10.858	2.905	3.738	<0.001	5.162	16.555
	Turung	11.311	2.812	4.022	<0.001	5.796	16.826
	Inpsprd	0.862	0.146	5.895	<0.001	0.575	1.149
	Inpsadmin	-0.798	0.157	-5.069	<0.001	-1.107	-0.489
	Inpshrm	1.156	0.173	6.680	<0.001	0.817	1.496

Table 19 presents the results of collinearity assessment using variance inflation factor (VIF) measurements. Notably, all VIF values exceeded 5, indicating a significant presence of multicollinearity among the predictive factors. This pronounced multicollinearity effect is evident through a considerable inflation of variance within the explanatory variables. As a result, this phenomenon introduces the risk of generating unreliable or unstable coefficient estimates for the model expressed by equation 21. The elevated VIF values further complicate the identification of genuine individual effects attributed to the explanatory variables.

Table 19. Collinearity results of explanatory variables

	Parameters	Collinearity Statistics			Collinearity Statistics	
		Tolerance	VIF		Tolerance	VIF
	Turnimp20	0.006	164.41		0.009	105.71
	Turnmar	0.003	361.71		0.004	275.83
	Turin	0.002	660.22		0.002	562.33
	Turung	0.000	2190.72		0.001	1512.72
	Inpsprd	0.094	10.65		0.094	10.61
Model 1	Inpslog	0.048	21.01	Model 2	0.053	18.99
	Inpsict	0.025	39.94		0.029	34.17
	Inpsadmin	0.018	55.66		0.038	26.48
	Inpsorgrel	0.029	34.00		0.033	30.32
	Inpshrm	0.049	20.47		0.103	9.71
	Inpsmkting	0.024	41.16		----	----

	Turimp20	0.020	49.00		0.021	48.29
	Turnmar	0.005	197.46		0.005	190.34
	Turin	0.002	552.68		0.002	535.01
	Turung	0.001	1197.63		0.001	1162.16
Model 3	Inpsprd	0.122	8.18	Model 4	0.122	8.17
	Inpsict	0.029	34.11		---	---
	Inpsadmin	0.088	11.37		0.144	6.94
	Inpsorgrel	0.034	29.71		0.044	22.50
	Inpshrm	0.117	8.55		0.136	7.35
	Turnimp20	0.021	47.88		---	---
	Turnmar	0.005	184.36		0.005	182.81
	Turin	0.002	509.07		0.002	460.53
	Turung	0.001	1113.86		0.001	1112.63
Model 5	Inpsprd	0.189	5.30	Model 6	0.201	4.97
	Inpsadmin	0.213	4.69		0.218	5.59
	Inpshrm	0.212	4.72		0.212	4.72

4.6 Discussion and Benchmarking

According to the obtained results, the product innovation output that generates the highest sales for firms is the improvement of products already existing in the firm's offering (Turnimp20). This form of product innovation leads to an average increase in sales of 7.6%. In contrast, the other studied product innovations result in an average increase of less than 1% in sales. This pattern could be attributed to the nature of the data used; new products introduced to the market or those recently added to the firm's offerings may potentially yield greater sales and revenues over an extended period. It's important to note that the survey collected information over a period of only three years, which might contribute to these findings.

Among the process innovations studied, the most frequently reported was Inpsict (52.4%), which pertains to the introduction of new data processing and communication systems. Information and Communication Technology (ICT) is widely recognized as a pivotal driver of a firm's capacity for innovative absorption (Najafi-Tavani et al., 2018). This is attributed to its support for various critical processes, including information gathering, data processing, real-time production evaluation, communication, customer and supplier interaction, enhanced decision-making, and knowledge creation (Kretschmer, 2012).

Among the analyzed R&D sectors, artificial intelligence demonstrated the highest performance percentage (13.8%). Remarkably, this value surpasses the combined sum of R&D studies reported in the biotechnology, biochemistry, and nanotechnology sectors. The inclination towards investing in R&D for artificial intelligence (AI) could be attributed to the expanding benefits of AI in automating processes. These benefits encompass data collection, analysis, interpretation, pattern recognition, and the development of tailored solutions to address specific firm needs (Enholm et al., 2022). Furthermore, there is evidence that investments in AI yield positive shifts in firm revenues (Lee et al., 2022). However, AI research was only positively correlated with increased sales for other relatively unchanged or slightly modified products, with an elasticity of less than 1.0.

Among the various efforts and investments made by firms to foster innovation, the highest average investments are directed towards total R&D expenses (Totrd20). This is followed by investments in machinery, equipment, software, or buildings (Invinno20), and other expenses related to innovations (Invoth20). Notably, the investments in Invinno20, Invoth20, and Totrd20 encompass both direct and indirect expenses related to ICT, such as software, hardware, or infrastructure, that support innovation and R&D activities.

The results indicate a non-homogeneous impact of explanatory variables on different types of product innovation outputs. The effects of explanatory variables encompassing measures of ICT (Invinno20, Invoth20, and Totrd20), as well as investments related to intellectual property, know-how, patents (Invpatent20), or market research during innovation launches (Invmarket20), do not significantly impact the developed models. Only for the sales from product innovation in relation to competitor offerings (Turmar), total R&D expenses (Totrd20) had a significant effect, but with a negative elasticity of -1.88E-9.

Despite the inability to establish the impact of ICT investments on most product innovation outputs at a 5% significance level, the results indicate positive coefficients or elasticities for Invoth20 and Totrd20 with sales from improved product innovations within your offering (Turimp20), Invinno20 and Invoth20 for sales from product innovations present in your offering but also offered by competitors (Turin), and Invinno20 and Totrd20 for sales from other mostly unchanged or slightly changed products (Turung). These findings suggest a potentially beneficial trend of this investment in the product innovation process.

The non-significant effects of these variables on product innovation outputs could be attributed to the lack of correction for endogeneity and simultaneity issues during the research, or to a potential complementarity effect between ICT investments and other factors. For instance, Matteucci & Sterlacchini (2004) found in their study that ICT intensity became significant only when a lag was introduced. To maximize the gains from ICT investments, they need to be complemented with investments in intangible assets and organizational changes.

In contrast to the models developed for product innovations, the effects of explanatory variables including measures of ICT (Invinno20, Invoth20, and Totrd20) revealed significant impacts in certain cases for process innovations. Notably, total R&D expenses (Totrd20) exhibit a significant positive elasticity for new production procedures (Inpsprd), accounting or administrative innovations (Inpsadmin), and marketing innovations (Inpsmkting) models. Furthermore, investments in machinery, equipment, software, and buildings for innovations (Invinno20) show a positive significant effect for the new marketing innovation model (Inpsmkting).

Despite the non-significant effects of some explanatory variables on most process innovation models, positive coefficients or elasticities are evident. Specifically, the variable Invinno20 demonstrates positive coefficients in new information processing or communication system (Inpsict), accounting or administrative process (Inpsadmin), process organization (Inpsorgrel), and organizational decision-making in human resources (Inpshrm) models. The variable Invoth20 exhibits positive coefficients in new production procedure (Inpsprd), logistics (Inpslog), and accounting or administrative process

(Inpsadmin) models, while the variable Totrd20 shows positive coefficients in logistics (Inpslog) and process organization (Inpsorgrel) models.

These outcomes also suggest a favorable impact of ICT investments on enhancing process innovation outputs. This finding is consistent with the findings of Polder et al. (2009) and Khalifa (2023), where ICT investments demonstrated a substantial contribution to process innovation outputs.

The model that best describes productivity intensity comprises six innovation outputs—three related to product innovations: the increase in sales from innovative products new in relation to competitors (Turmar), sales from innovative products already offered by competitors but also in your offer (Turin), and sales from other relatively unchanged or slightly modified products (Turung); and three corresponding to process innovations: new methods or production procedures (Inpsprd), new accounting or administrative processes (Inpsadmin), and new organization of decision-making in human resources (Inpshrm).

Firm productivity is notably enhanced by product innovations compared to process innovations. An increase of one unit in Turmar, Turin, and Turung leads to improvements of 15.230, 10.858, and 11.311 lnPI units, respectively, under the assumption of other model parameters remaining constant. In contrast, process innovations generally yield elasticities of less than 1.2 units, with Inpsadmin displaying a negative value of -0.798. The observed negative outcome for new accounting or administrative processes (Inpsadmin) might be associated with the time required to discern a positive impact on firm productivity. In the short term, the implementation of novel administrative procedures could potentially disrupt daily operations and necessitate staff training, implying that positive outcomes may be achieved in the long term.

Product innovations exert a predominantly positive influence on firm productivity intensity, overshadowing the impact observed from process innovations. Additionally, Also Hall, (2011) found empirical evidence indicating that product innovations had a more economically significant effect on productivity, whereas the impact of process innovations was more ambiguous. One possible explanation for this outcome is the challenge of accurately measuring the true quantity effect or intensity of process innovations.

Returning to the research question, it becomes evident that ICT investments achieved a more pronounced and favorable influence on process innovation compared to product innovation. This inclination can be attributed to their pivotal role in facilitating diverse functions, including data collection, analysis, processing, logistics, and other integral aspects of firm operations. ICT investments can drive process innovations by increasing efficiency, data-driven understandings, helping collaborative activities and facilitating the access to information (Kretschmer, 2012).

However, firm productivity is more significantly enhanced by product innovation. Several factors can influence this finding. Product innovations often lead to new or improved offerings, which can result in increased market share, competitive advantage, and consequently, higher revenues for firms. This direct impact on revenue becomes a driving force for prioritizing product innovations. Additionally, the visibility of product innovations to customers tends to be higher compared to process innovations. This visibility can influence customer retention and brand recognition positively.

The impact of process innovation on firms' productivity could be more difficult to quantify and their final effect more complex to elucidate. Process innovations might involve changes on internal operations, potentially indicating a riskier effort and demanding substantial initial investments. In fact the new accounting or administrative process studied, evidenced negative impact on firm's productivity.

Nevertheless, it is imperative to acknowledge that the potential of process innovations to enhance productivity should not be underestimated. While product innovations may yield more visible and immediate outcomes, the impact of process innovations can be far-reaching. They possess the potential for substantial efficiency gains, cost reductions, and optimized resource allocation over the long term.

4.7 Managerial Implications

The findings of this dissertation offer valuable insights into potential managerial implications, which can be summarized as follows:

1. <u>Strengthen Collaborative Efforts</u>: The impact of R&D activities and collaboration on process innovation has been conclusively demonstrated. As such, managers are encouraged to foster a culture of collaboration both within and outside the organization. By fostering synergistic interactions across diverse departments or teams, a robust platform for knowledge exchange and interdisciplinary projects can be cultivated, amplifying the collective expertise.
2. <u>Empower Staff through Training and Skill Development</u>: The introduction of the new accounting or administrative process seemingly yielded an initial decrement in firm productivity, potentially attributed to the transitional period required for the positive impact to materialize. In the short term, the adoption of novel administrative processes might disrupt established daily operations and necessitate staff training. This implies that the realization of favorable outcomes could be more apparent in the long term. Managers should identify skill gaps and focus in training and skill development programs for employees, to maximize the benefits of the technology adoption and to increase the firm's knowledge capital.
3. <u>Performance Tracking</u>: While the evaluation of process innovation outcomes employed binary variables, it's essential to recognize that this approach might not fully capture the complete impact of these innovative activities. A more comprehensive perspective could be attained by considering parameters beyond binary categorizations. For instance, quantifying the cost reductions from newly introduced process innovations and conducting a long term assessment of their effects could provide a better understanding. Managers are encouraged to leverage ICT tools to establish a robust performance tracking mechanism, providing insights to make informed decisions and refine strategies for sustained growth and optimization.
4. <u>Innovation and New Product Development</u>: Firms' productivity was greatly enhanced by product innovation. ICT investments can accelerate the innovation process by enabling simulation and collaboration processes. Managers could foster cross-functional teams to

amplify ICT's impact on innovative product and service development. As ICT investments demonstrated a substantial impact on process innovation, managers should facilitate bottleneck identification, process reengineering, and continuous improvement initiatives.

5. Measuring Process Innovation Impact: Manager should establish and improve metrics to measure the impact of ICT adoption on product and process innovation. By developing comprehensive measurement frameworks, firms can systematically evaluate the outcomes of ICT integration, gaining insights into effectiveness and areas for enhancement.

5 Conclusions

The present exploratory research uses a parametric approach to examine the impact of Information and Communication Technologies (ICT) on firms' productivity. The study found a relationship between firms' innovation efforts, including ICT investments, product and process innovation outputs, and ultimately, the firm's productivity. The results are a clear motivation to further study the impact of innovation outcomes on firms’ productivity.

The main conclusions from this research can be summarized as follows:

- The product innovation output with the most significant impact, leading to increased sales for firms, is the enhancement of existing products within the firm's portfolio (Turnimp20), resulting in an average sales increase of 7.6%. Other types of product innovations, however, generate a comparatively modest average sales increase of less than 1%. Among the seven process innovations studied, the most frequently reported one was the implementation of new data process and communication systems (Inpsict), accounting for 52.4% frequency among all firms studied.
- The findings reveal a lack of uniform impact among explanatory variables across different types of product innovation outputs. The explanatory variables including ICT measures (Invinno20, Invoth20, and Totrd20) and investments related to IP, know-how, patents (Invpatent20), or market research (Invmarket20) do not significantly impact the developed product innovation models, except for the total R&D expenses (Totrd20), which negatively affects the product innovation related to competitor offerings (Turmar).
- In the context of process innovation models, the impact of explanatory variables including ICT measures (Invinno20, Invoth20, and Totrd20) is more varied. Total R&D expenses (Totrd20) exhibit a significant positive elasticity in new production procedures (Inpsprd), accounting or administrative systems (Inpsadmin), and marketing (Inpsmkting) innovation models. Furthermore, investments in machinery, equipment, software, and buildings (Invinno20) significantly influence the new marketing innovation model (Inpsmkting). Despite the non-significant impact of some explanatory variables on most process innovation models, positive coefficients or elasticities are observed in several cases, indicating a satisfactory effect of ICT investments on enhancing process innovation outputs.
- The most representative model illustrating the relationship between productivity intensity and innovation outputs is derived through a backward linear regression method. Among the innovation outputs, six are found to have significant effects on productivity intensity. Three of these are associated with product innovations: the percentage of sales from product innovation new in relation to competitor offerings (Turmar), the percentage of sales from product innovation already present in the firm's portfolio but also offered by competitors (Turin), and the percentage of sales for other relatively unchanged or slightly modified products (Turung). The remaining three correspond to process innovations: new processes or production methods (Inpsprd), new accounting or administrative systems (Inpsadmin), and new organization of decision-making in human resources (Inpshrm).
- Notably, firm productivity experiences greater enhancement through product innovations compared to process innovations. A one-unit increase in Turmar, Turin, or Turung leads to

productivity intensity improvements of 15.230, 10.858, and 11.311, respectively, while keeping other model parameters constant. Conversely, the effect of process innovation on firm productivity intensity remains below 1.2 units.

6 Recommendations for Further Research

The present study serves as an exploratory research that allows to spot the influence of ICT adoption on firm productivity. Future research should expand upon the current dissertation, aiming for more confirmatory results, and taking into consideration the following pivotal aspects:

- Addressing Endogeneity and Simultaneity: Correcting the biases caused by endogeneity and simultaneity is crucial, as these issues often impact research findings. Instrumental variables could be employed for this purpose, involving the utilization of historical R&D and ICT investment data. Employing longitudinal data can facilitate the correlation between present and past R&D and ICT investments, yielding more robust results.
- Exploring Complementarity Effects: Studying complementary effects among different types of investments and innovation outputs would provide a deeper understanding of their combined impact on firm productivity.
- Sector-Specific Studies: Conducting sectoral analyses would enable homogeneity testing and exploration of the effects of explanatory variables across various sectors.
- Enhanced Modeling: Future studies should aim to develop improved models, potentially by integrating the firm's capital stock into the Cobb-Douglas production function. It is important to note that the current productivity equation explains only a modest 7% of the variability in the responses, and there is a significant presence of high collinearity among the independent variables.
- Individual ICT Investment Effects: Exploring the specific impacts of ICT investments within the CDM model and analyzing how they contribute to different aspects like hardware and software investments would provide a more detailed insight into their influence.

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