# Corporate investment and the labour market in Portugal

Tese de Doutoramento

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Doutoramento em

**Ciências Económicas e Empresariais**

Ponta Delgada
2025

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Tese especialmente elaborada para obtenção do grau de Doutor em Ciências Económicas e Empresariais, com especialização em Economia.

## ABSTRACT

This study examines the determinants of corporate investment and its impact on labour productivity and employment levels in Portuguese companies. Using a combination of administrative and survey data, the key drivers behind corporate investment decisions are identified and how these investments influence labour productivity and employment dynamics are evaluated. The results show that financial leverage, growth potential, and firm age play a significant role in investment decisions, with evidence of a U-shaped relationship between age and investment rates. The analysis further demonstrates a positive relationship between investment and labour productivity, highlighting the important role of sustained investment in raising productivity levels. In addition, the findings reveal that investment and R&D expenditures significantly increase employment opportunities, particularly for skilled workers with tertiary education, supporting the notion that knowledge-intensive, high-skill industries are important to skilled employment growth. The results contribute to the existing literature by providing empirical insights specific to the Portuguese context and offer important considerations for policymakers and business leaders. A strategy that combines targeted support for R&D-intensive industries with policies that promote skills development could both encourage productive specialisation and help retain skilled workers in Portugal.

Keywords: corporate investment; labour productivity; employment; econometric analysis; Portuguese companies.

# RESUMO

Este estudo analisa os fatores determinantes do investimento empresarial e o seu impacto na produtividade do trabalho e nos níveis de emprego nas empresas portuguesas. Utilizando uma combinação de dados administrativos e de inquéritos, identificam-se os principais fatores subjacentes às decisões de investimento das empresas e avalia-se a forma como esses investimentos influenciam a produtividade do trabalho e a dinâmica do emprego. Os resultados mostram que a alavancagem financeira, o potencial de crescimento e a idade da empresa desempenham um papel significativo nas decisões de investimento, com provas de uma relação em forma de U entre a idade e as taxas de investimento. A análise demonstra ainda uma relação positiva entre o investimento e a produtividade do trabalho, salientando o importante papel do investimento sustentado no aumento dos níveis de produtividade. Além disso, os resultados revelam que o investimento e as despesas em I&D aumentam significativamente as oportunidades de emprego, em especial para os trabalhadores qualificados com formação superior, apoiando a noção de que as indústrias com utilização intensiva de conhecimentos e elevadas qualificações são importantes para o crescimento do emprego qualificado. Os resultados contribuem para a literatura existente, fornecendo informações empíricas específicas para o contexto português e oferecem considerações importantes para os decisores políticos e líderes empresariais. Uma estratégia que combine um apoio direcionado para as indústrias de I&D intensiva com políticas que promovam o desenvolvimento de competências poderia incentivar a especialização produtiva e ajudar a reter trabalhadores qualificados em Portugal.

Palavras-chave: investimento empresarial; produtividade do trabalho; emprego; análise econométrica; empresas portuguesas.

# DEDICATORY

I dedicate this work to my grandparents, who taught me from a young age the importance of education in understanding the world, and showed me, with great patience and love, that there are no limitations to pursuing a dream, seeking more out of life, and being happy.

# ACKNOWLEDGMENTS

To Professor José António Cabral Vieira, for his support and availability, assertive advice, and constant encouragement, which greatly enhanced the challenge and improved the depth and clarity of the research.

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# LIST OF ABBREVIATIONS

AR – Autoregressive

CAE Rev. 3 – Portuguese Classification of Economic Activities, Revision 3

EU – European Union

FE – Fixed Effects

GDP – Gross Domestic Product

GMM – Generalized Method of Moments

GVA – Gross Value Added

IBAS – Integrated Business Accounts System

ICT – Information and Communication Technology

IT – Information and Technology

LPM – Linear Probabilistic Models

LSDVC – Least Squares Dummy Variable Corrected

n.e.c. – not elsewhere classified

NSTPS – National Scientific and Technological Potential Survey

NUTS – Nomenclature of Territorial Units for Statistics

OLS – Ordinary Least Squares

pp – percentage points

R&D – Research and Development

SME – Small and Medium Enterprise

TFP – Total Factor Productivity

UK – United Kingdom

USA – United States of America

# CHAPTER I – INTRODUCTION

The role of corporate investment in the context of the labour market is a critical issue within the disciplines of economics and business. Investment is recognised as a foundational element in the pursuit of economic growth and development. Such investment facilitates capital accumulation, fosters innovation, and enhances productivity, thereby contributing to the overall economic prosperity of a nation (Solow, 1956; Romer, 1990; Aghion & Howitt, 1992; Foster et al., 2001; Bloom et al., 2012). Within the corporate sector, investment decisions are influenced by numerous factors, including financial leverage, market conditions, and policy environments, among others (Jensen, 1986; Myers, 1977; Aivazian et al., 2005; Andersen et al., 2016).

Despite the existence of numerous studies in the international literature on the determinants of corporate investment, there remains a degree of consensus and a degree of disagreement. For instance, certain empirical studies have highlighted a consistent negative correlation between leverage and investment, thereby indicating that higher levels of debt can constrain firms' investment capabilities (Jensen, 1986; Myers, 1977; Aivazian et al., 2005; Andersen et al., 2016). However, it should be noted that this relationship is not generalizable, as evidenced by the divergent results observed across various European countries (Martinez-Carrascal & Ferrando, 2008).

Labour productivity, which is defined as the Gross Value Added (GVA) per unit of labour, is a crucial component of economic performance. This measure reflects how efficiency labour inputs are used in the production process and is significantly affected by investment activities. Investments in physical capital, technology, and human capital are essential for driving productivity improvements (Solow, 1956; Romer, 1990; Psacharopoulos & Patrinos, 2004; Acemoglu & Robinson, 2012; Bloom et al., 2014).

The level o employment is closely related to both investment and productivity. The creation of new jobs is a primary goal of economic policy, and understanding the factors that drive employment levels is essential for designing effective interventions (Freeman & Soete, 1994; Piva & Vivarelli, 2005; Aiello & Cardamone, 2009; Bogliacino & Vivarelli, 2012). In this context, the Lisbon Strategy highlights the importance of innovation in promoting economic growth and expanding employment opportunities (European Commission, 2005).

However, the relationship between investment and employment, particularly in the context of technological innovation, is complex and multifaceted. Although technological advancements have been shown to stimulate job creation (Autor et al., 2003; Acemoglu & Autor, 2011), they can also lead to job displacement and an increased demand for high-skilled labour. This duality underscores the need for nuanced and context-specific analysis, especially in economies with structural particularities such as Portugal.

The present research aims to provide a comprehensive analysis of corporate investment behaviours and their consequent effects on labour productivity and employment levels in Portuguese companies from 2010 to 2019. Using a variety of econometric models and extensive datasets, this research contributes to the understanding of investment decision-making and its broader economic impacts. It attempts to elucidate the determinants of investment within the context of Portuguese companies, providing information on how financial structures and other factors influence investment decisions.

The primary objective of the research is to examine the factors that influence corporate investment decisions in Portugal and to analyse whether and how these investments impact labour productivity and employment levels. The study is structured around three core subjects, namely investment determinants, identifying the key factors that drive investment decisions in Portuguese companies, investment and labour productivity, exploring the relationship between these two variables, and investment and employment level, investigating the impact of investment on employment, with a special focus on the role of investment in Research and Development (R&D) activities.

This research makes several contributions to the empirical analysis because it provides empirical evidence on the determinants of corporate investment in Portugal, highlighting the roles of leverage, company size, and growth potential. It also explores the relationship between investment and labour productivity, analysing how investment and R&D expenditures drive employment, particularly for highly skilled workers. The present research uses a unique combination of administrative datasets, including the Integrated Business Accounts System (IBAS) and the Single Report, complemented by survey data from the Scientific and Technological Potential Survey, covering approximately 380,000 companies annually from 2010 to 2019.

The findings have the potential to be of relevance both for academics and society at large. For policymakers, these insights can serve as a guide in the formulation of policies that encourage investment, foster innovation, and promote qualified employment. For business leaders, an understanding of the determinants and impacts of investment can inform strategic decisions about resource allocation and workforce development.

The work has been organised into six chapters, each addressing a specific aspect of the research question. Chapter II provides a comprehensive review of the existing literature on the determinants of investment, the relationship between investment and productivity, and the link between investment and employment. Chapter III analyses the factors influencing investment decisions using several econometric models and data at company level. Chapter IV explores the impact of investment on labour productivity, considering both physical and human capital. Chapter V investigates how investment and R&D affect employment across different educational levels. Finally, Chapter VI summarises the key findings, discusses their implications, and suggests directions for future research.

# CHAPTER II – LITERATURE REVIEW

This chapter plays a fundamental role in the theoretical foundation of the research, providing a comprehensive and critical analysis of the existing contributions on the relevant topics. It begins with a review of the literature on the main determinants of business investment, followed by an exploration of the relationship between investment and productivity in companies, and ends with a presentation of the key literature related to investment and employment.

## 2.1 Investment determinants

In the literature, a consensus exists that leverage and investment are negatively correlated at the firm level. However, recent years have seen an increased focus on households, individuals, and the financial industry, diverting attention from non-financial firms, as seen in Andersen et al. (2016). For example, they found that highly leveraged individuals significantly reduced their consumption in the 2008-2012 crisis period compared to their low-leveraged counterparts. This illustrates the negative impact of leverage on consumption behaviour.

One line of reasoning suggests that highly leveraged companies can operate below optimal investment levels due to economic deterioration or liquidity constraints, resulting in a negative relationship between leverage and investment (Lang et al., 1996; Myers, 1977). Similarly, Aivazian et al. (2005) argue that companies that anticipate future investment opportunities might reduce their leverage to avoid constraints on future financing.

Jensen (1986) introduced the concept of "overinvestment", where companies can present growth despite having low-quality investment projects. This strategy can make the firm vulnerable, especially if it requires substantial cash flow to meet debt obligations. In this case, a negative relationship between leverage and investment should be expected, particularly for companies with limited growth opportunities or with greater restrictions on access to bank credit or financial markets.

The post-2007 global contraction in investment is attributed to limited access to finance and increased uncertainty (International Monetary Fund, 2015). During this period, financial institutions tightened the lending criteria, making it more difficult for companies to secure the necessary funding for investment projects. Furthermore, the global economic downturn led to higher uncertainty, causing firms to adopt a more cautious approach to capital expenditure. The reluctance to invest was further exacerbated by declining consumer confidence and reduced demand, creating a challenging environment for businesses. The combined effect of these factors resulted in a significant reduction in overall investment levels, preventing economic recovery and growth.

Banerjee et al. (2015) identified uncertainty about expected profits and the future state of the economy as the primary drivers of investment behaviour. Uncertainty plays an important role in investment decisions because it causes firms to be more cautious and delay their investments (Bloom et al., 2007).

Micro-level data analysis revealed differences in the leverage-investment relationship between countries. Martinez-Carrascal and Ferrando (2008) identified a negative relationship in Belgium, France, and, even to a lesser extent, Italy, contrasting with Germany and the Netherlands. Holmberg (2013) examined Swedish companies, noting that those with low credit reserves reduced investment more than others, indicating a link between credit reserves and investment decisions.

Campa and Shaver (2002) emphasise the importance of liquidity in investment decisions. They say that in the presence of liquidity restrictions, firms with stable cash flows are more likely to exhibit robust investment behaviour. Their results highlight exporting companies as examples of this trend, indicating a positive relationship between investment and exports. This implies that, in the context of liquidity constraints, companies engaged in export activities tend to maintain more consistent and stable investment patterns.

In contrast, Mofrad (2012) presents findings that diverge from those mentioned before. In his work, a positive and significant long-term relationship can be observed between the gross domestic product (GDP), investment, and exports. However, unlike previous studies, he identified a negative relationship between investment and exports. This discrepancy underlines the complexity and variability in the relationships between economic variables, highlighting the need for nuanced analyses to understand the dynamics of investment behaviour and its connections to broader economic indicators.

Methodological considerations are crucial in investment studies. Bond (2002) contributed to this field using an autoregressive (AR) model, that is, an AR(1) model, to explain the investment. His findings highlight potential biases in commonly used estimators. According to him, the Ordinary Least Squares (OLS) estimator, particularly for large samples, exhibits a positive bias due to the correlation between the explanatory variable and the error term. He also mentioned that, although the Fixed Effect (FE) estimator eliminates unobserved heterogeneity, it introduces biases in the AR(1) model, pulling estimates in an opposite direction to the previous estimate. These insights caution against the indiscriminate application of certain estimators and emphasise the importance of considering model-specific aspects.

Aivazian et al. (2005) employed a set of alternative models, including an instrumental variable approach. The goal is to address the endogeneity problem inherent in the relationship between the variables under study, leverage and investment. The authors strategically incorporate instrumental variables to mitigate potential biases in estimating causal relationships. They go a step further by considering various determinants and testing multiple theories, contributing to the knowledge of the relation between leverage and investment.

Lang et al. (1996) and McConnell and Servaes (1995) used the OLS estimator to analyse investment behaviour. However, Aivazian et al. (2005) and Bond (2002) warned against the indiscriminate use of OLS regression. They argued that relying solely on OLS can lead to an underestimation of the impact of explanatory variables, particularly due to the oversight of firm heterogeneity. This highlights the evolving methodological considerations in the field and the need for more nuanced approaches to capture the complexities of investment dynamics.

Serrasqueiro et al. (2011) built upon the methodology introduced by Aivazian et al. (2005). Using a dynamic panel estimator, they examined a sample of 222 Portuguese companies. The choice of a dynamic panel estimator reflects the acknowledgement of the dynamic nature of investment decisions. Despite the relatively small sample size, they yield compelling insights. They employ the Generalised Method of Moments (GMM) estimator from Arellano and Bond (1991) and the Least Squares Dummy Variable Corrected (LSDVC) estimator from Bruno (2005), providing an analytical framework to capture the dynamic aspects in investment analysis.

Furthermore, Mendes et al. (2014) examined a group of Portuguese small and medium enterprises (SMEs) by conducting a comprehensive analysis using two different samples categorised by age. The first group comprises 582 young SMEs, while the second group includes 1,654 older SMEs. They used a dual-method approach that combines a two-step estimation method and quantile regressions. The study reveals insights into the determinants of investment in these two age-defined SME groups, indicating that the age of the enterprises is important to explain investment. This approach allows for a more granular understanding of the various factors influencing investment decisions in different age groups. However, the authors refer to a constraint in their analysis, as they had not considered the degree of relationship between the companies and their creditors in their model. This omission highlights a potential opportunity for further exploration, indicating that future research could benefit from considering the relationship between enterprises and creditors. Furthermore, the study implies that differentiating between various types of debt issued by companies and expanding the sample size could enhance the depth and generalisation of the findings.

Nunes et al. (2014) gave a particular exploration of investment determinants within Portugal. They conducted a case study within the fitness industry, employing various regression models. The study consistently acknowledges the presence of fixed effects in their analyses. Consequently, they opted for the Arellano and Bond (1991) estimator, recognising its efficacy in accounting for fixed effects. This methodological choice aligns with the focus on addressing potential endogeneity concerns and contributes to the robustness of their findings within the specific context of the fitness industry.

Examining the broader spectrum of investment determinants, Williams (2007) introduced a new perspective by proposing a general binary investment model, arguing that investment decisions are influenced by the social performance of companies. To support this claim, the study applies a survey in five countries – Australia, Canada, Germany, the UK and the USA. By centring the analysis on the impacts of social aspects, his work contributes to a growing understanding of the potential influence of social performance on investment behaviour.

Martinez-Carrascal and Ferrando (2008) contributed to the perspective of the cross-country literature using data from six countries. Their analysis points to a negative relationship between leverage and investment, particularly pronounced in countries such as Belgium and France, and to a lesser extent, Italy. Moreover, they did not verify this relationship in Germany and The Netherlands. The estimation involved the system GMM estimator, incorporating techniques from both Arellano and Bover (1995) and Blundell and Bond (1998). This nuanced examination highlights the importance of considering regional variations and diverse economic contexts when exploring the relationship between leverage and investment.

Campa and Shaver (2002) indicated that companies that show stable cash flows tend to manifest more robust investment patterns when faced with liquidity constraints. Their findings indicate a positive relationship between investment and exports, particularly highlighting the regular investment behaviour of exporting companies. To model investment as a latent variable, given its observability only in the positive state, the authors employ a Tobit model. This methodological choice reflects their tentative attempt to capture the complexities of investment behaviour in the context of liquidity constraints.

Taking a different approach with a focus on regional data, Lim (2014) conducted a vast analysis with data covering a panel of 129 countries. The author explores various factors that influence investment activity on this broad scale. Methodologically, the study employs the System GMM estimator, drawing on techniques from Arellano and Bover (1995) and Blundell and Bond (1998). This methodological choice reflects a strong framework for capturing the nuances of investment dynamics across different regions, emphasising the author's commitment to a comprehensive understanding of the multifaceted determinants of investment.

In the economic literature, there are several perspectives to tackle the relationship between leverage and investment, drawing insights from an array of studies across different industries, regions, and methodological approaches. In particular, Aivazian et al. (2005), Bond (2002), and Serrasqueiro et al. (2011) emphasised the importance of employing advanced econometric methods, including instrumental variable approaches and dynamic panel estimators, to address endogeneity concerns and capture the dynamic nature of investment decisions.

Regional nuances and industry-specific analyses, as demonstrated by studies such as Martinez-Carrascal and Ferrando (2008) and Lim (2014), further highlighted the need for a contextualised understanding of these dynamics. While some studies, such as Campa and Shaver (2002), examined the impact of liquidity restrictions on investment, others, such as Williams (2007) and Nunes et al. (2014), expanded the discussion by exploring the influence of social performance and industry-specific determinants. This review provides a solid foundation for empirical investigation into factors that shape investment decisions within the Portuguese context, as proposed in this research.

## 2.2 Investment and labour productivity

The dynamics of labour productivity and business investment have long been essential for economic research and policy considerations (Solow, 1956; Romer, 1990; Aghion & Howitt, 1992). Understanding the complex interplay between these variables is crucial for fostering economic growth, innovation, and competitiveness. This review of the literature examines the intricate relationship between these two variables, drawing insights from key academic works, theoretical frameworks, and empirical evidence from enterprises.

The neoclassical growth model of Solow (1956) served as a foundation to understand investment-led growth theories. This model indicates that sustained economic expansion results from the accumulation of physical capital. Increased investments in machinery, infrastructure, and other forms of capital expenditures are identified as catalysts for improved productivity, consequently driving economic growth. The Solow model highlights the initial substantial impact of capital accumulation with diminishing returns, which requires ongoing investments for sustained growth.

Romer (1990) extended the neoclassical framework by introducing endogenous technological change. Using Solow's exogenous view of technological progress, Romer argues that investments in R&D and human capital lead to endogenous technological advancements. According to the author, businesses actively engaged in innovation can generate sustained and long-term economic growth by contributing to the accumulation of knowledge and ideas.

Aghion and Howitt (1992) went deeper into Romer's ideas by introducing the concept of "creative destruction". They argued that economic growth consists of the constant destruction of outdated technologies and the creation of new and more efficient ones. Investments in innovation support this creative destruction process, leading to higher productivity and economic growth. Acemoglu and Robinson (2012) explored the role of institutions in shaping investment-led growth. Their work emphasises that inclusive institutions, which provide a level playing field and protect property rights, are crucial to fostering sustained investment and economic development.

Piketty (2014) offered a contemporary perspective on the relationship between capital accumulation and economic growth. His work emphasises that returns on capital often exceed the rate of overall economic growth, leading to a rise in wealth inequality. This insight has important implications for understanding the effects of investment-led growth theories on wealth distribution.

Although investment-led growth theories have provided valuable insight into the drivers of economic expansion, they have also faced critiques, and extensions have emerged. Lucas (1988) questioned the assumptions of the Solow model, highlighting the need for more nuanced considerations of human capital and technological progress. Other research explores the impact of globalisation and environmental sustainability on investment-led growth theories, clarifying the broader economic landscape (Jones, 2016; Acemoglu, 2009).

Investment-led growth theories, beginning with Solow's neoclassical model and extending to later contributions by Aghion and Howitt (1992), Acemoglu and Robinson (2012), and Piketty (2014), have significantly enriched the understanding of the dynamics between investment, productivity, and economic growth. These theories acknowledge the multifaceted nature of capital accumulation, emphasising the importance of innovation, institutions, and the evolving economic landscape. As the topic continues to develop, researchers struggle with the challenges of adapting these theories to contemporary issues such as technological disruption, income inequality, and sustainability concerns.

Empirical evidence constitutes a basis for understanding the complex dynamics between business investment and labour productivity. Numerous studies, at both the industry and company levels, have empirically examined the correlation between investment decisions and their subsequent impact on productivity outcomes. Empirical research at the industry level consistently confirms the positive correlation between business investment and labour productivity. The impact of investing in physical assets, advanced technologies and technological innovations, as well as the improvement of human knowledge, skills, and abilities, has been demonstrated in the literature (Black & Lynch, 2001).

Foster et al. (2001) presented an industry-level analysis, supporting the idea that companies actively engaging in capital expenditure not only achieve efficiency gains but also see marked improvements in overall productivity. This finding highlights the fundamental role of investment decisions in shaping the dynamics of entire industries, influencing competitiveness, and contributing to economic growth (Syverson, 2011).

Additionally, this aligns with the argument that a company's productivity increases with the cumulative aggregate investment in an industry, where increasing returns rise because new knowledge is considered an investment (Arrow, 1962). Additional insights from Stiroh (2000) emphasised the neoclassical theory, such as the Solow model, where technological change is considered an exogenous variable. However, Ding and Knight (2009) criticised the assumptions of the Solow model, questioning the exclusivity of technological progress as the sole driver of economic growth.

Expanding this perspective, Bloom et al. (2012) emphasised the critical role of organizational capital and skilled labour in amplifying the effects of technological adoption. They concluded that while new technologies can enhance productivity, their success depends on complementary inputs within the organisational framework.

Moreover, the research conducted by Bloom et al. (2013) provided additional depth to the industry-level perspective. Their study explored the impact of investments in information and communication technology (ICT) on productivity across industries. The findings revealed significant variability in the returns on ICT investments, emphasising the need to consider the nature of capital expenditure to better understand its impact on productivity dynamics.

Research at the company level, exemplified by the insights provided by Bartelsman et al. (2013), went beyond general analyses, focusing on specific facets such as innovation and technology to uncover how targeted investments drive higher rates of productivity growth. This empirical research offers insight into the relationship between investment strategies and productivity outcomes, shaping the understanding of how businesses and industries evolve in response to strategic capital allocation.

Their research went beyond a general analysis, specifically investigating the role of innovation and technology in driving productivity growth. They provided evidence that companies at the forefront of technological advancements and those investing strategically in innovation exhibited significantly higher rates of productivity growth. These results highlight the importance of making specific investment decisions, particularly in areas like R&D and technology adoption, which can substantially influence a firm's productivity trajectory (Cohen & Levinthal, 1990).

While Medda and Piga (2014) emphasised the positive impact of tangible investment on labour productivity, confirming that there is a lag-distributed effect of such investments, Bloom et al. (2014) examined the relationship between management practices, including the investment in human capital through training, and firm performance. This indicates that well-managed firms that invest in workforce training tend to be more productive.

Brynjolfsson and Hitt (2000) examined the relationship between information technology (IT) investment and business performance. They discuss how IT investments can lead to productivity gains by enabling organisational transformation and improving business processes. This confirms the insights of Cette et al. (2016), who note that the use of ICT leads to capital deepening, subsequently boosting labour productivity. The different findings across studies indicate that the impact of tangible investment on labour productivity depends on context, changing not only with economic development levels but also with industry-specific rates of tangible investment, environmental factors, and corporate behaviour. This highlights the need for nuanced empirical analyses, such as the one proposed in this research, to reach specific conclusions about the effects of tangible investment on labour productivity in Portuguese companies.

Furthermore, some literature addresses the issue of complementarity between physical capital and human capital, stating that the interaction between these two variables positively influences the productivity of companies. Past research on this complementarity stresses the vital interplay between these two variables, revealing their collective influence on enhancing the productivity of companies. Aghion and Howitt (1992) highlighted the synergistic nature of investments in both physical and human capital, emphasising the importance of considering the joint impact of these capital inputs on overall productivity.

Arora and Gambardella (1990) focused on the biotechnology industry, providing insight into the complementarity between a firm's internal physical capital and its external partnerships. Their study shows how the positive interaction between these elements contributes to increased firm productivity, especially in innovative industries where external collaborations are crucial.

Benhabib and Spiegel (1994) offered a comprehensive theoretical and empirical overview, emphasising the positive influence of human capital accumulation on economic growth, measured by the level of education. Their work underscores the relationship between physical and human capital, revealing them as complementary drivers of productivity and economic development.

In Peng et al. (2020), the intricate relationship between innovation, human capital, and financial constraints is explored. Their study provides insights on how investments in human capital, aligned with innovation efforts, play a crucial role in overcoming financial constraints and fostering productivity. This adds a layer of complexity to the understanding of complementarity, particularly in the context of firms facing financial challenges.

Taking into account empirical evidence, Schmiedeberg (2008) contributed to the literature by examining the complementarity of innovation activities in the German manufacturing industry. The study indicates that there is a positive interaction between investments in R&D and human capital, highlighting their joint contribution to firm-level innovation and, consequently, productivity. Acemoglu and Angrist (2000) examined the complementarity between training programs (representing human capital development) and the adoption of technology within firms. Their study provides empirical evidence of how the simultaneous investment in employee training and the adoption of technology positively influences firm productivity, emphasising the synergy between these capital inputs.

The discussion of the complementarity between physical and human capital has provided valuable insights, particularly from Maksimovic and Phillips (2002). Their exploration of conglomerate firms and their resource allocation strategies across industries provided a distinctive perspective through which to understand complementarity. Regarding the efficiency of resource allocation within conglomerates, the study provides theoretical and empirical evidence on how firms manage various capital and human resources in multiple industries.

These studies emphasise the importance of understanding how both types of capital, physical and human, jointly influence productivity. This understanding is crucial for companies in different industries that want to improve their productivity. Despite the prevailing view in the economic literature that emphasises the complementarity between physical and human capital in shaping the productivity of companies, a different perspective has emerged in certain studies. This line of research challenges the assumption that investments in both types of capital necessarily lead to a synergistic relationship that uniformly enhances productivity. Some of these studies are presented in the following paragraphs.

Card and DiNardo (2002) argued that standard knowledge, in terms of skill-biased technological change may not fully explain the observed trends in the labour market. Instead of assuming complementarity between physical and human capital, Krueger (1993) raised concerns about the rising wage inequality associated with technological advancements, indicating that the benefits may not be evenly distributed among workers. Hanushek (2003) examined the efficacy of input-based schooling policies, challenging the straightforward link between investments in education (representing human capital) and enhanced productivity. The research highlighted the complexity of the relationship, arguing that the impact of human capital on productivity depends on various factors.

Elsby et al. (2013) contributed to the literature by challenging the traditional notion that variations in the capital-to-labour ratio lead to shifts in the labour share. Their general equilibrium model indicates that factors beyond physical capital, such as technological improvements, play a more substantial role in influencing the distribution of income. Crouch et al. (1999) argued against the simplistic view that increasing the level of skill of the workforce (human capital) will inevitably lead to increased productivity. They emphasise the importance of the institutional context, indicating that the coordination between education and training systems is crucial in determining the effectiveness of skill-training policies.

These studies provided an alternative perspective, indicating that the relationship between physical and human capital and its impact on productivity is more complex than a straightforward complementarity. They highlighted the need to consider contextual factors, institutional frameworks, and the distributional effects of capital investments when analysing their influence on company productivity. This perspective challenges researchers and policymakers deeper investigate the capital-productivity connection in diverse economic settings.

Another important trend in the literature is that the qualification of human capital in companies is important for understanding productivity (Mankiw et al., 1992). This study explored the role of human capital, particularly education, in contributing to economic growth, implying that investments in education lead to an accumulation of human capital, fostering technological progress and productivity improvements. Their research underlined the importance of education as a driver of overall economic development.

Psacharopoulos and Patrinos (2004) provided insights into the positive correlation between higher educational attainment and productivity outcomes. Their research emphasised the economic benefits of investing in education, as it not only enhances individual skills but also contributes to broader societal productivity. Hanushek and Woessmann (2012) extended this discussion by examining the global implications of educational quality on productivity. Their work highlighted the importance of the quality of education, measured by cognitive skills, in shaping the economic success of nations. The positive association between educational quality and productivity results underscores the broader socio-economic impact of educational investments.

These studies supported the idea that higher education levels are positively correlated with increased productivity. Whether through the accumulation of human capital, the improvement of individual skill, or the quality of education provided, the evidence from these references highlights the importance of educational investments in driving productivity. The thesis explores the potential complementarity between physical and human capital in the context of companies in Portugal. This analysis is prompted by the existing literature indicating such complementarity in various countries.

The relationship between physical and human capital is of crucial importance in the context of understanding and enhancing productivity in business operations. In examining this relationship, the focus is on the manner in which these two forms of capital interact and contribute to the apparent labour productivity of companies. The following survey elucidates the multifaceted nature of this relationship, drawing insights from the literature in this field.

Some literature revealed that collaborative interaction between advanced technology and a skilled workforce promotes greater efficiency and innovation, as presented in Arrow (1962) and Black and Lynch (2001). This indicates that physical capital, including machinery, technology, and infrastructure, often relies on skilled human capital for optimal use. Furthermore, the alignment of human capital with physical capital requirements, as emphasised by Becker (2009), is fundamental to driving productivity gains through skill use and adaptability.

The central role of human capital in driving technological progress, as highlighted in Romer (1990), emphasised the significant influence of the knowledge and creativity of the workforce on the development and use of physical capital. Similarly, operational excellence, as discussed by Roth and Menor (2003), is based on the expertise of the workforce, as well-trained and skilled employees contribute to operational excellence, minimise errors, and maximise productivity.

The quality of production is significantly influenced by human capital, as noted by Bresnahan et al. (2002), and skilled workers improve both the quantity and the overall quality of the products or services produced. Companies that cultivate a harmonious relationship between physical and human capital, as proposed by Porter (1998), gain a competitive advantage, enabling efficient production processes, fast adaptation to technological changes, and continuous improvement of the workforce.

Barro and Sala-i-Martin (2014) argued that long-term sustainability is intricately linked to sustained investment in both physical and human capital, ensuring the competitiveness and adaptability of companies within evolving market dynamics. Lucas (1988) discussed the crucial role of human capital in resource allocation and decision making. Human capital provides the intellectual capacity needed to make effective decisions about the allocation of physical capital. This highlights its contribution to strategic decisions on investments in technology, equipment, and infrastructure.

Understanding the relationship between physical and human capital, as supported by several authors, enables companies to adapt to technological advancements, maximise productivity and ensure long-term success in today's dynamic business environment. The literature review highlights the intricate and complex connection between business investment and productivity dynamics. Theoretical foundations emphasise the relevance of investments in capital and innovation, and this is substantiated by empirical evidence from both industry and firm levels.

## 2.3 Investment and employment level

The discussion of the impact of investment on employment is complex. In this comprehensive review of the literature, the various forms of innovation are examined, alongside their direct and indirect effects on employment. The literature review also addresses challenges and compensation mechanisms. Ortega-Argilés et al. (2011) provided an in-depth review of the empirical literature on the effect of spending on research and development (R&D) on employment and production. They highlight the positive relationship between innovation investment and economic growth, emphasising the consequences that can impact labour market dynamics.

At the company level, Entorf and Pohlmeier (1990) and Brouwer et al. (1993) conducted empirical analyses, revealing how the introduction of new products can create jobs, while innovations in production processes can displace them. However, these analyses may suffer from a "positive bias", as innovative companies tend to outperform others in the labour market.

Industry-specific studies by Antonucci and Pianta (2002) and Evangelista and Savona (2002) explored the effects of technological change, highlighting significant variations between manufacturing and services. Although innovation may negatively impact employment in manufacturing, knowledge-intensive industries, such as information technology, biotechnology, and financial services, can experience positive effects.

However, the effects of innovation investment on employment are complex and varied. Studies differ on the effects of innovation, with some research indicating an increase in the employment of unskilled workers due to technological innovation (Dutz et al., 2011), while others highlight a growing demand for skilled labour (Brynjolfsson & McAfee, 2012; Brynjolfsson & McAfee, 2016).

Martin (1998) analysed the information industry in the USA between 1970 and 1995 and observed an expansion in the number of workers. Despite technological advances that lead to declining growth rates, the workforce in this industry still increased. This growth was driven by the rapid adoption of new technologies and the growing demand for information services. However, the study also noted that while some jobs were created, others were displaced due to automation and improved efficiency. In general, the information industry demonstrated resilience and adaptability, with a net positive impact on employment.

Autor et al., 2003, Goos and Manning (2007), and Acemoglu and Autor (2011) have investigated how technology, specifically computing, affects the content of tasks in the labour markets of the USA and the UK. These studies conclude that routine jobs can be automated by robots or computers, whereas computing capital is complementary to non-routine tasks. This implies that while automation can displace certain types of employment, it also enhances the productivity of more complex, non-routine tasks that require human intervention.

Further research has found a positive association between innovation and employment level in high-tech industries, although this relationship does not hold in the low-tech and service industries (Buerger et al., 2012; Van Roy et al., 2018). Furthermore, investment in innovation can benefit managers, but negatively affect office and manual workers (Cirillo, 2017). These studies reveal the importance of considering industry differences when analysing the impact of investment on employment.

Other studies indicate that technology replaces routine tasks while complementing non-routine tasks, mirroring trends observed in the USA (Ikenaga & Kambayashi, 2016; Fukao et al., 2017). This shift highlights the increasing importance of skills that involve complex problem solving, creativity, and interpersonal communication, which are less susceptible to automation. As a result, the demand for highly skilled workers is expected to increase, leading to potential changes in the composition of the workforce and training requirements. These trends support the need for policies that support the adaptation of the workforce to technological advancements, ensuring that workers are equipped with the necessary skills to thrive in an evolving job market.

Business investment is frequently related to innovation and is considered a key factor in the creation of new products, services, processes, and technologies. Aiello and Cardamone (2009) demonstrate how investment in R&D may increase innovation and, consequently, employment growth. Using empirical data, they demonstrate a positive correlation between R&D expenditure and company performance.

Bogliacino et al. (2012) examined the effects of R&D expenditures on company performance, using panel data estimators to analyse European microdata. The results indicate that companies that invest significant resources in innovation tend to experience stronger employment growth. These findings highlight the importance of policies designed to incentivise investment in R&D by encouraging companies to allocate more resources toward it.

Technological innovation plays a crucial role in determining employment patterns in companies. Freeman and Soete (1994) analysed the impacts of automation and digitalisation on the labour market, emphasising the need for policies that promote the workers' adaptation to technological changes. In addition to investing in technology, investing in human capital is also crucial for employment growth. Piva et al. (2005) and Piva and Vivarelli (2005) highlighted the importance of improving skills to improve the employability and productivity of companies.

Several additional studies further contribute to the understanding of the relationship between investment in innovation and employment dynamics. Bogliacino and Vivarelli (2012) used a dataset that covered 25 manufacturing and service industries in 15 European countries from 1996 to 2005, using GMM-SYS panel estimations to analyse the effect of R&D expenditure on employment. Their findings align with previous literature, indicating that R&D expenditure, particularly in product development innovation, has a job-creating effect.

Ciarli et al. (2018) investigated the impact of firms' investment in R&D on employment levels and composition in the local labour markets of the UK. They found that although R&D growth does not necessarily lead to a general increase in local employment, it does influence employment composition, particularly in areas with different initial levels of routinisation.

Shah et al. (2024) focused on Japan's efforts to boost its economy through innovation, analysing a panel of businesses in 33 industries to examine the impact of R&D activities on employment. Their results show a positive association between innovation and employment gains, especially in the manufacturing industry, aligning with the compensation theory. These findings offer insights for policymakers looking to promote technological development in Japan and potentially other countries facing similar demographic and macroeconomic challenges.

Despite insights from company-level and industry analyses, these approaches have limitations. Company-level analyses are susceptible to a "positive bias" phenomenon (Entorf & Pohlmeier, 1990; Brouwer et al., 1993), in which innovative firms, driven by their inherent dynamism, may exhibit better performance metrics, potentially skewing the observed effects of innovation on employment. Similarly, industry analyses, while revealing industry-specific impacts of technological change, often fail to fully capture the intricate interplay and spillover effects between industries, thus potentially overlooking the general impact of innovation on employment dynamics (Piva & Vivarelli, 2005).

Macroeconomic studies face their own set of challenges in accurately measuring technological change and accounting for the many institutional factors that shape the landscape of the labour market (Autor et al., 2003). The dynamic nature of technological progress, coupled with the diverse array of institutional frameworks across different economies, poses significant methodological difficulties for macroeconomic analyses seeking to understand the relationship between investment in innovation and employment outcomes.

Although the relationship between technological change and employment is complex and multifaceted, empirical analyses offer valuable insights to understand its effects in the Portuguese case, as proposed in this research. In fact, it is important to acknowledge the limitations and challenges of these analyses and to continue research to obtain a more complete and accurate understanding of the impacts of technological change on the Portuguese labour market.

# CHAPTER III – INVESTMENT DETERMINANTS IN PORTUGUESE COMPANIES

Corporate investment decisions are essential in shaping the economic trajectories of businesses and the broader economy. In a dynamic and complex global financial landscape, understanding the determinants of such investment is critical. The research in this domain has repeatedly highlighted the intricate relationship between leverage, potential growth, and specific characteristics of the companies such as age, size, ownership structure, or industry, with numerous studies documenting their varied impacts on investment levels (Andersen et al., 2016; Aivazian et al., 2005; Myers, 1977; Jensen, 1986). However, the diversity of these findings raises essential questions about their generalizability, particularly in economies like Portugal, which exhibit unique structural and institutional characteristics.

The role of leverage as a critical determinant of investment is well established in the literature. Myers (1977) first identified the constraints leverage imposes on firms' ability to exploit future investment opportunities, followed by Jensen (1986), who emphasized the risks of overinvestment in firms with substantial free cash flow. These first ideas have been expanded through empirical studies by Lang et al. (1996) and Aivazian et al. (2005), which reveal a negative relationship between leverage and investment. However, this relationship is not universally consistent. For example, Martinez-Carrascal and Ferrando (2008) demonstrated variations across European countries, highlighting the significant influence national economic contexts on investment dynamics.

Portugal offers a particularly interesting context for examining investment determinants due to its economic evolution over the past decade. Following the 2008 global financial crisis, Portuguese firms faced heightened uncertainty, reduced access to finance, and a contraction in consumer confidence, factors that significantly influenced their investment behaviours (International Monetary Fund, 2015; Banerjee et al., 2015). The structural characteristics of the Portuguese economy, marked by a prevalence of small and medium-sized enterprises (SMEs), further highlight the need for context-specific research. Mendes et al. (2014) and Serrasqueiro et al. (2011) have stressed the distinct investment behaviours of Portuguese small and medium enterprises (SMEs), including their sensitivity to age, growth opportunities, and financial constraints.

Despite the increasing literature on investment determinants, critical gaps remain in understanding how these factors manifest within the Portuguese context, especially when leveraging advanced econometric techniques like dynamic panel models. Previous research, such as that by Nunes et al. (2014), provides valuable insights into industry-specific determinants of investment. However, there is a pressing need for broader analyses that capture the interplay between firm-specific characteristics, and investment decisions across various industries.

This chapter aims to address these gaps by employing anonymized data on Portuguese companies, covering approximately 380,000 companies annually from 2010 to 2019. The analysis spans all industries, excluding financial and insurance activities and public administration and defence. The richness of this dataset allows for a comprehensive examination of the factors influencing corporate investment, including financial leverage, export levels, revenue generation capacity, and company age.

In light of the aforementioned considerations, the objective of this chapter is to identify the factors influencing Portuguese companies' investment decisions. To this end, several estimation methods were employed, along with the anonymised data provided by Statistics Portugal. The database of Portuguese companies spans the period from 2010 to 2019, encompassing approximately 380,000 companies annually. The analysis covers the industries A[1] to S[2], known as economic activity sectors, excluding financial and insurance activities (section K), and public administration and defence, compulsory social security (section O), as per the Portuguese Classification of Economic Activities – Revision 3 (CAE Rev. 3)[3]. Further details about the database are provided in Section 3.2.

By applying a dynamic panel model with System Generalized Method of Moments (GMM) estimation, this study contributes to the methodological discourse on investment analysis. The approach accounts for the dynamic nature of investment decisions while addressing potential biases inherent in other estimators. Moreover, this work integrates findings from a diverse body of literature, offering a nuanced understanding of investment behaviours in a post-crisis and in a SME-dominated economy.

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[1] Agriculture, forestry and fishing.

[2] Other service industries.

[3] According to the structure published in Decree-Law no. 381/2007, of 14th November.

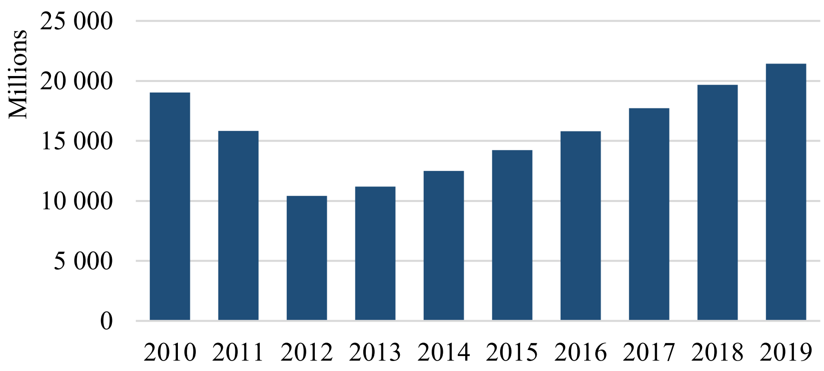
The chapter is organised as follows. Section 3.1 offers a background on company investment. Section 3.2 explains the source and data used. Section 3.3 presents the econometric model and the estimation methods. Section 3.4 uncovers the major empirical findings. Finally, Section 3.5 summarises the key conclusions and presents some remarks.

## 3.1 Background

This section employs simple descriptive statistical tools to characterise the behaviour of the main variable, net investment of non-financial companies in Portugal, from 2010 to 2019. The analysis focuses on the group of companies used for econometric applications in this chapter, presenting results at the regional, size class[4], and economic industries.

Figure 1 illustrates the net investment of companies between 2010 and 2019, revealing a peak in 2019 at €21.4 billion, representing a growth of 12.7% compared to 2010. The lowest point occurred in 2012, approximately €10.4 billion, with a recovery in subsequent years.

Figure 1. Aggregate net investment by companies in Portugal (values in million euros, 2012 prices)



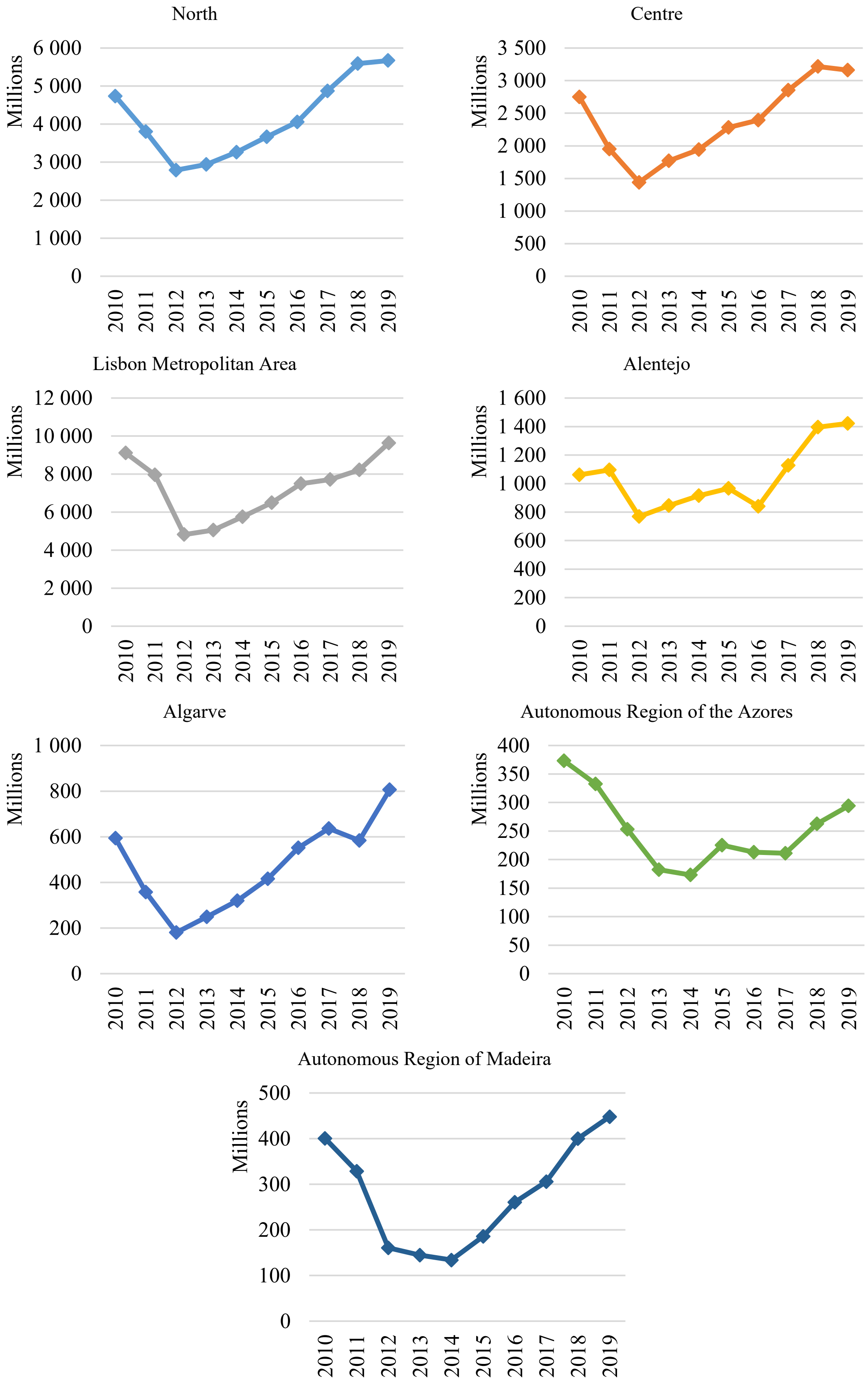

Source: Authors' calculations based on data from IBAS, Statistics Portugal.

Figure 2 plots the net investment results per NUTS 2 region[5] from 2010 to 2019. From 2010 to 2012, investment has been reduced in all regions, with the Lisbon Metropolitan

[4] The classification of enterprise size was based on the adaptation of the Commission Recommendation of May 6, 2003 (Recommendation no. 2003/361/CE) concerning the definition of micro, small and medium-sized enterprises, transposed into national legislation by Decree-Law no. 372/2007, of November 6, 2007.

[5] The Nomenclature of Territorial Units for Statistics (NUTS) was developed by Eurostat and employed in both Portugal and the entire European Union for statistical purposes.

Figure 2. Aggregate net investment by companies in Portugal, by NUTS 2 regions (values in million euros, 2012 prices)




Source: Authors' calculations based on data from IBAS, Statistics Portugal.

Area registering a reduction of €4.3 billion. The Algarve registered the highest percentage decrease, at 69.7%. However, between 2010 and 2019, most regions experienced a growth in investment, ranging from 5.7% in the Lisbon Metropolitan Area to 35.6% in the Algarve. In contrast, the Autonomous Region of the Azores recorded a 21.1% reduction.

Table 1 highlights the industrial composition of the total investment of the companies in 2010 and 2019, together with the corresponding changes. Among the industries with the greatest weight in total investment in 2019, the manufacturing industry exhibited a substantial increase, representing 25.5% in 2019 of total investment, an increase of 7.3 pp from 2010. Similarly, the distributive trade industry registered growth, comprising 18.7% of total investment in 2019, 6.8 pp more compared to 2010.

Of particular importance is the information and communication industry, which recorded a 79.1% growth in investment between 2010 and 2019. The agriculture and fishing industry also showed a substantial growth, recording an increase of 61.7%. These two industries achieved the highest relative growth rates during this period. In contrast, the energy and water, transportation and storage, and accommodation and food services industries registered decreases of 41.8%, 36.4% and 36.3%, respectively, in total investment between 2010 and 2019.

Table 1. Share of industry in total corporate investment in 2010 and 2019, and percentage change of the investment between 2010/2019 (%)

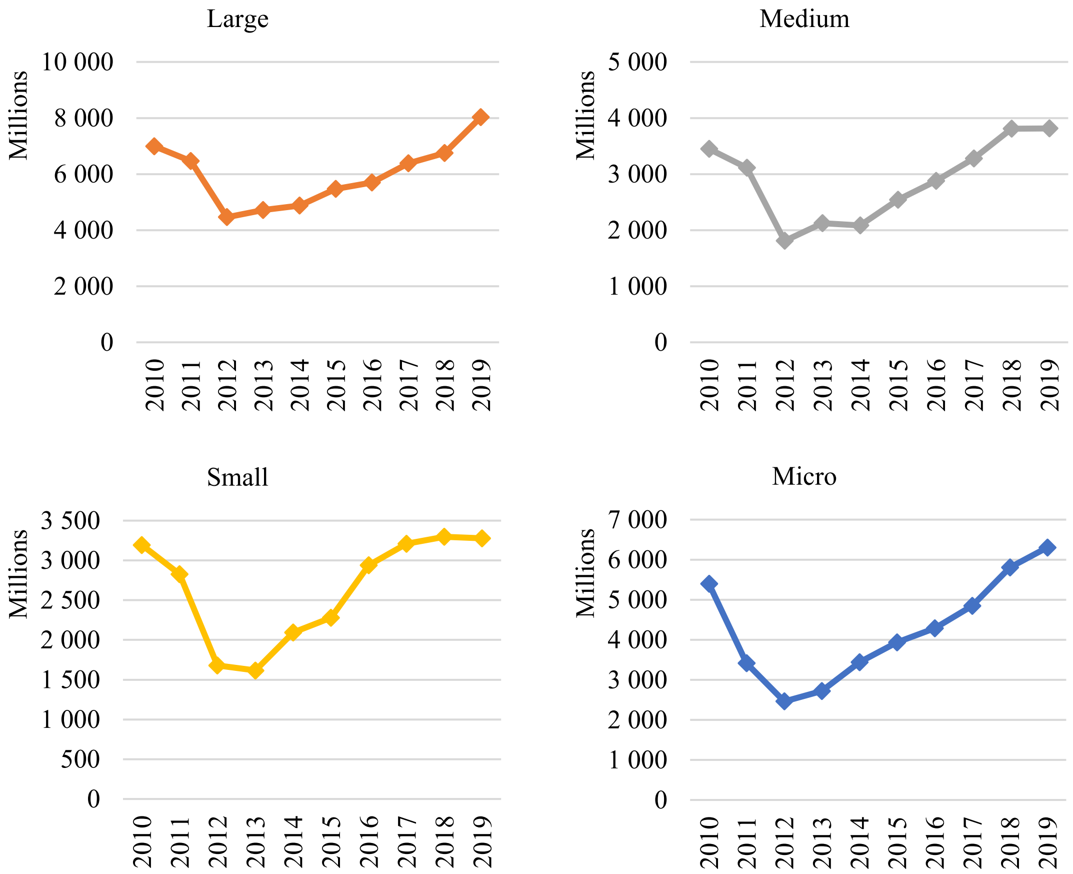
| Industry | Correspondence to the CAE Rev. 3 | Share of total investment (%) | | Change in the share (pp) | Rate of change of investment (%) |
|---|---|---|---|---|---|
| | | 2010 | 2019 | 2010/2019 | 2010/2019 |
| Agriculture and fishing | A | 2.8 | 4.6 | 1.8 | 61.7 |
| Manufacturing | B, C | 18.2 | 25.5 | 7.3 | 39.9 |
| Energy and water | D, E | 16.3 | 9.5 | -6.8 | -41.8 |
| Construction and real estate | F, L | 12.5 | 13.9 | 1.4 | 11.3 |
| Distributive trade | G | 11.9 | 18.7 | 6.8 | 57.0 |
| Transportation and storage | H | 10.4 | 6.6 | -3.8 | -36.4 |
| Accommodation and food services | I | 9.8 | 6.2 | -3.6 | -36.3 |
| Information and communication | J | 5.3 | 9.5 | 4.2 | 79.1 |
| Other services | L, M, N, P, Q, R, S | 12.7 | 18.1 | 5.4 | 42.3 |

Source: Authors' calculations based on data from IBAS, Statistics Portugal.

Figure 3 illustrates the evolution of net investment by companies categorised by size class, based on the number of persons employed, turnover, and net assets over the period 2010-2019. In 2019, large companies contributed approximately €8 billion to net investment, corresponding to 37.5% of the total amount, compared to €7 billion, or 36.7%, in 2010.

Micro-sized companies accounted for the second highest value of net investment, reaching €6.3 billion and representing 29.4% of total investment in 2019 (compared to €5.4 billion, or 28.4%, in 2010). Small and medium companies maintained comparable net investment values throughout the period, accounting for 15.3% and 17.8% of the total investment in 2019, respectively (compared to 16.8% and 18.1% in 2010). Between 2010 and 2012, micro-enterprises experienced the highest decrease in investment (-54.4%), while large enterprises registered the lowest decrease (-36.1%). Small and medium companies registered decreases of 47.4% and 47.6%, respectively.

Figure 3. Aggregate net investment by companies in Portugal, by dimension (values in million euros, 2012 prices)




Source: Authors' calculations based on data from IBAS, Statistics Portugal.

## 3.2 Data

The data used in the analysis of this chapter were provided by Statistics Portugal and have previously been authorised by the Directorate General for Education and Science Statistics. The data source is the Integrated Business Accounts System (IBAS), which results from the integration of statistical information on businesses. This integration is heavily based on administrative data, particularly the Simplified Business Information (IES)[6]. According to the Instituto Nacional de Estatística (2022), the central objective of the IBAS is to characterise the economic and financial behaviours of companies. This characterisation involves a set of variables of significant relevance to the business sector, including key financial ratios commonly used in corporate financial analysis.

Recognising the considerable variation in characteristics between companies and individual enterprises, the analysis is focuses on companies. This choice is due to the observation that individual enterprises exhibit distinct behavioural patterns and offer a narrower range of economic and financial indicators, this distorting the research. Thus, the database used includes a total of 676,382 distinct companies operating in industries A to S, excluding financial and insurance activities (industry K), and public administration and defence, compulsory social security (industry O), according to CAE Rev. 3[7]. This dataset spans over a decade, covering the years 2010 to 2019, resulting in a total of 3,869,726 observations throughout the entire period.

The temporal evolution of the dataset revealed some fluctuations. In 2019, the database comprised 438,923 active companies, representing a significant increase from the 361,229 companies present in 2010. 2012 recorded the lowest number of active companies at 355,731, compared to the peak registered in 2019. The annual average is around 380,000 companies.

The selection of variables for analysis aims to identify the determinants of companies investment, drawing on information from the existing literature (Andersen et al., 2016; Jensen, 1986; Serrasqueiro et al., 2011). These variables include a variety of factors,

[6] The IES (Simplified Business Information) was created in 2007 with the aim of simplifying companies' compliance with their legal obligations. It consolidates several statements and annual accounts for accounting, tax and statistical purposes into a single submission, as established in the Portuguese Decree-Law no. 8/2007, of 17 January 2007, in its current version.

[7] The Portuguese Classification of Economic Activities (CAE Rev. 3), approved by the Portuguese Decree-Law no. 381/2007, of November 14, 2007.

including financing conditions, export levels, revenue generation capacity, company age, employment levels, and turnover. They are strategically chosen to align with established insights and empirical findings (Aivazian et al., 2005; Campa & Shaver, 2002; Lim, 2014).

The dependent variable is the investment rate, defined as the ratio of investment in the current period to capital stock in the previous period, in agreement with the established literature on investment determinants (Mendes et al., 2014; Serrasqueiro et al., 2011). Investment corresponds to the gross fixed capital formation, representing the acquisitions minus the disposals of fixed assets during the period. Fixed assets are tangible or intangible assets resulting from production processes, that are used repeatedly or continuously in the production process for a period that exceeds one year.

In line with insights from the existing literature, the choice of explanatory variables in the models includes turnover, which serves as a proxy for the scale and industry of the company (Bond, 2002). Return on sales, although initially considered for its potential as a profitability measure, did not show statistical significance in the final model and thus has been omitted (Aivazian et al., 2005). The level of exports is included to identify potential behaviour differences between exporting and non-exporting firms (Campa & Shaver, 2002). Furthermore, although the risk profile was not statistically significant in any of the regressions, its inclusion aims to account for variations in risk exposure (Mendes et al., 2014).

The econometric analysis further stratifies companies based on industry, categorising them into nine groups: agriculture and fishing, manufacturing, energy and water, construction and real estate, distributive trade, accommodation and food services, transportation and storage, information and communication, and other services.[8]

A geographical breakdown is also considered, accounting for the location of the company's head office within the seven NUTS 2 regions of Portugal: North, Centre, Lisbon Metropolitan Area, Alentejo, Algarve, Autonomous Region of the Azores, and Autonomous Region of Madeira.

The company size classification adapts the European Commission's recommendation of May 6, 2003, which defines micro, small, medium, and large enterprises based on the

[8] For each industry corresponds to one or more sections of the CAE Rev. 3.

number of persons employed. This classification provides a nuanced understanding of the size of the company, facilitating more granular analyses of investment determinants within distinct strata of the business landscape.

Table 2 provides an overview of the descriptive statistics of the main variables of the database. The primary reason for using these data is not only the quantity of information available but also its quality, since it comes from an official source. With more than 3 million observations covering 676,382 distinct companies, the dataset provides a solid foundation for a reliable analysis. The average annual investment in these companies is approximately €41,530. The correlation matrix reveals low levels of correlation, indicating that there are no issues with strong correlations between the explanatory variables.

Table 2. Main descriptive statistics

| Variable | Units | Mean | Median | Standard deviation | No. observations |
|---|---|---|---|---|---|
| Net investment | € | 41,530 | 0 | 1,692,446 | 3,799,280 |
| Debt ratio | % | -16 | 0 | 56,579 | 3,783,425 |
| Percentage of exports | % | 6 | 0 | 20 | 3,310,576 |
| Growth of turnover | % | 446 | 0 | 132,748 | 2,798,012 |
| Tangible assets | € | 22 | 9 | 111 | 3,758,347 |
| Risk profile | ratio | -2,806 | 1 | 561,544 | 3,819,711 |
| Cash flow | € | -153 | 3 | 19,359 | 3,758,347 |
| Logarithm of turnover | Log of € | 12 | 11 | 2 | 3,355,985 |
| Logarithm of the persons employed | Log of No. | 1 | 1 | 1 | 3,869,726 |

Source: Authors' calculations based on data from IBAS, Statistics Portugal.

### 3.3 The econometric model

This section introduces the estimated model, incorporating an autoregressive term as expressed by the following equation:

$$y_{i,t} = \beta_0 + \beta_1 \cdot y_{i,t-1} + \beta_i \cdot x_{i,t-1} + \beta_3 \cdot x_{i,t} + \eta_i + \upsilon_{i,t} \tag{3.1}$$

$$i = 1, \dots, N$$

$$t = 1, \dots, T$$

where $y_{i,t}$ represents the dependent variable, which is the investment rate of the company $i$ in period $t$ ($invrate_{i,t}$), and $y_{i,t-1}$ is the observation of the same variable that refers to the same company in the previous period ($invrate_{i,t-1}$) as an explanatory variable. Similarly, $x_{i,t-1}$ and $x_{i,t}$ represent the vectors of the explanatory variables of company $i$ in periods $t-1$ and $t$, respectively. The term $\eta_i$ captures the unobserved heterogeneity constant over time, and $v_{i,t}$ represents the error term.

Explanatory variables also include the level of indebtedness of the company in the previous period ($debt_{i,t-1}$), measured by the ratio of non-current liabilities to equity; the company's exports in the previous period ($export_{i,t-1}$), acting as a proxy for growth opportunities, as exporting companies have a larger potential market; and the sales growth rate in the previous period ($gturn_{i,t-1}$), which serves as an additional indicator of the growth opportunities of the company.

The tangibility of the company's assets in the previous period ($tngassets_{i,t-1}$) was quantified by the ratio of tangible fixed assets to total assets, providing a measure of the level of collateral the company can offer to its creditors. Furthermore, it included a proxy for the company's risk profile in the previous period ($risk_{i,t-1}$), determined by the ratio of equity to GVA.

The ratio of net income plus depreciation to the total assets of the company in the previous period provides an indication of the funds generated by the company's activities ($cashflow_{i,t}$). Furthermore, the company's turnover in the previous period serves as a proxy for its size ($turn_{i,t-1}$).

The age and age squared of the company in the reference period are included to enable the modelling of age effects non-linearly, rather than assuming a linear for all ages ($age_{i,t}$ and $age^2_{i,t}$, respectively). The model also included dummy variables for the number of persons employed (4 groups), industry (9 groups), geographical location at NUTS 2 level (7 regions) and year.

### 3.3.1 Estimation methods

This section discusses different estimation methods considering that the equation to be estimated includes the lag of the dependent variable as an explanatory variable. The OLS estimator, as described by Bond (2002), tends to produce positively biased results, especially for large samples, due to the correlation between the explanatory variable $y_{i,t-1}$ and the error term ($\eta_i + v_{i,t}$). The FE estimator, while eliminating unobserved heterogeneity ($\eta_i$), introduces bias in the opposite direction. It preserves consistency only under the conditions of a large sample size and a fixed number of time periods, assuming that all variables on the right side of Equation (3.1) are strictly exogenous.

This leaves two other estimators: the difference GMM and the system GMM. The choice between them involves considerations presented in the literature, often guided by two rules of thumb. The first rule of thumb, articulated by Blundell and Bond (1998), states that if the dependent variable is persistent and closely resembles a random walk (i.e. the parameter of the lagged dependent variable approaches one ($\beta_1 \rightarrow 1$)), the difference GMM estimator can produce biased and inefficient estimates of $\beta_1$ in finite samples, especially with a short time span. Blundell and Bond (1998) explain these problems as being due to the use of poor instruments. To address this problem, they proposed the use of the system GMM estimator.

The second rule of thumb, introduced by Bond et al. (2001), recommends initial estimating the autoregressive model using pooled OLS and FE. The pooled OLS estimate for $\beta_1$ should be considered an upper bound estimate, whereas the fixed effects estimate represents a lower bound estimate. If the difference GMM estimate approximates or falls below the fixed effects estimate, it indicates that the former is downward biased due to weak instruments. Consequently, the system GMM estimator is recommended.

Several studies support the superiority of the system GMM estimator over the difference GMM estimator. Roodman (2009) argued that the system GMM estimator provides more efficient estimates in dynamic panel data models, particularly when addressing endogeneity and instrument relevance issues. Arellano and Bover (1995) highlight that the system GMM estimator helps overcome the weak instrument problem associated with the difference GMM estimator by employing additional moment conditions.

Holtz-Eakin et al. (1988) contributed significantly to the discussion on addressing endogeneity concerns in panel data models. Their work emphasises the importance of controlling for endogeneity, which can arise from omitted variables, measurement errors, or simultaneity. They provide important insights into the challenges associated with estimating dynamic panel models, particularly highlighting the difficulties in obtaining consistent and unbiased estimates when endogeneity is not properly addressed.

Each estimation method has different advantages and disadvantages. OLS is computationally straightforward but may be biased. FE eliminates unobserved heterogeneity, but introduces bias if the exogeneity assumptions are violated. The difference GMM is suitable for persistent variables but may suffer from weak instrument issues. The system GMM is recommended for overcoming weak instrument problems, although it requires additional instruments and may be computationally intensive. The selection of the estimator should align with the characteristics of the data and the assumptions of the model. The literature, particularly the works of Roodman (2009) and Arellano and Bover (1995), provides valuable information on the performance of these estimators under various conditions, guiding researchers in selecting the most appropriate approach for their specific context.

## 3.4 Estimation results

Table 3 presents the estimation results with the investment rate as the dependent variable. Since the lagged investment rate is also included as an explanatory variable in the models, its coefficient should be interpreted with reference to the explanations provided in the previous section.

Regarding the autoregressive element of the model, the investment rate in the previous period, the second rule of thumb proposed by Bond et al. (2001) is confirmed. This implies that the estimation results obtained from the system GMM estimator are more appropriate. This recommendation arises because the pooled OLS estimator tends to produce a positively biased estimation, given that the explanatory variable $y_{i,t-1}$ is correlated with the error term $(\eta_i + \upsilon_{i,t})$, while the FE estimator provides a negatively biased estimation (0.0544 against 0.0126, respectively).

Although the coefficient estimated by the difference GMM is statistically significant, it remains below the FE estimate (0.0126 versus 0.0053, respectively), implying a potential negative bias. According to Bond et al. (2001), the preferable choice in this situation is the system GMM estimator. This aligns with findings in the practical application illustrated by Blundell and Bond (2000), who employed a Cobb-Douglas production function in a sample of 703 UK firms.

Table 3. Model estimates for investment rate

| Dependent variable: $invrate_{i,t}$ | Pooled OLS (1) | | | FE (2) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $invrate_{i,t-1}$ | 0.0544 | 0.0139 | *** | 0.0126 | 0.0018 | *** |
| $debt_{i,t-1}$ | -0.0004 | 0.0001 | *** | -0.0003 | 0.0000 | *** |
| $export_{i,t-1}$ | 0.0084 | 0.0011 | *** | 0.0396 | 0.0127 | *** |
| $gturn_{i,t-1}$ | 0.0008 | 0.0001 | *** | 0.0009 | 0.0004 | ** |
| $tngassets_{i,t-1}$ | -0.0019 | 0.0016 | | -0.0012 | 0.0010 | |
| $risk_{i,t-1}$ | 0.0001 | 0.0001 | | 0.0001 | 0.0001 | |
| $cashflow_{i,t}$ | 0.0010 | 0.0001 | *** | 0.0016 | 0.0006 | *** |
| $turn_{i,t-1}$ | 0.0450 | 0.0124 | *** | 0.0044 | 0.0015 | *** |
| $e1t9_{i,t-1}$ | - | - | - | - | - | - |
| $e10t49_{i,t-1}$ | -1.9092 | 0.5439 | *** | -2.0131 | 1.3298 | |
| $e50t249_{i,t-1}$ | -1.5834 | 0.4528 | *** | -2.2527 | 2.5020 | |
| $ege250_{i,t-1}$ | -0.8410 | 0.4271 | | -3.4009 | 2.4942 | |
| $age_{i,t}$ | -0.0149 | 0.0018 | *** | -0.2373 | 0.0744 | *** |
| $age^2_{i,t}$ | 0.0018 | 0.0002 | *** | 0.0038 | 0.0019 | ** |
| $agrc_{i,t}$ | - | - | - | - | - | - |
| $manf_{i,t}$ | 0.5843 | 0.0527 | *** | 3.5559 | 0.3601 | *** |
| $enrg_{i,t}$ | -0.0486 | 0.0435 | | -0.5629 | 0.0581 | *** |
| $cons_{i,t}$ | 0.9687 | 0.0634 | *** | 0.1798 | 0.0378 | *** |
| $trad_{i,t}$ | 0.8079 | 0.0496 | *** | 0.3046 | 0.0274 | *** |
| $tran_{i,t}$ | 3.6095 | 0.1162 | | 0.2746 | 0.3617 | |
| $infr_{i,t}$ | 0.6366 | 0.0993 | *** | 0.7005 | 0.0660 | *** |
| $accm_{i,t}$ | 3.1606 | 0.2403 | *** | 1.8123 | 0.1856 | *** |
| $othr_{i,t}$ | 0.1414 | 0.0462 | *** | 0.2955 | 0.0331 | *** |
| $north_{i,t}$ | 0.1569 | 0.0938 | * | 0.4357 | 0.1424 | *** |
| $centre_{i,t}$ | 0.3386 | 0.1025 | *** | -0.1589 | 0.0833 | * |
| $lisbon_{i,t}$ | 0.3078 | 0.0903 | *** | 0.9548 | 0.1610 | *** |
| $alentejo_{i,t}$ | -0.3573 | 0.1054 | *** | -0.4916 | 0.2970 | * |
| $algarve_{i,t}$ | 0.3699 | 0.0944 | *** | -0.6156 | 0.0950 | *** |
| $azores_{i,t}$ | - | - | - | - | - | - |
| $madeira_{i,t}$ | 0.1280 | 0.1164 | | 0.1012 | 0.0901 | |

Table 3. (continuation)

| Dependent variable: *invrate*$_{i,t}$ | Pooled OLS (1) | | | FE (2) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| *2012*$_i$ | - | - | - | - | - | - |
| *2013*$_i$ | 0.5528 | 0.7565 | | - | - | - |
| *2014*$_i$ | 1.6348 | 0.7171 | *** | 0.8947 | 0.1569 | *** |
| *2015*$_i$ | 1.7285 | 0.5360 | *** | 0.9945 | 0.2335 | *** |
| *2016*$_i$ | 1.3733 | 0.5047 | *** | 0.5994 | 0.3097 | * |
| *2017*$_i$ | 1.8009 | 0.3982 | *** | 0.8914 | 0.3781 | *** |
| *2018*$_i$ | 2.2777 | 0.7574 | *** | 1.4875 | 0.4600 | *** |
| *2019*$_i$ | 2.3725 | 0.4687 | *** | 1.7050 | 0.5385 | |
| *constant* | -0.1190 | 1.0117 | | 14.6155 | 18.9510 | |
| R-squared | 0.5201 | | | 0.548 | | |
| Observations | 1,840,068 | | | 2,189,633 | | |
| m1 | -2.63 | | | -2.32 | | |
| m2 | -1.69 | | | -1.03 | | |
| Sargan | - | | | - | | |
| Instruments | - | | | - | | |

Table 3. (continuation)

| Dependent variable: $invrate_{i,t}$ | Difference GMM (3) | | | System GMM (4) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $invrate_{i,t-1}$ | 0.0053 | 0.0020 | *** | 0.0421 | 0.0123 | *** |
| $debt_{i,t-1}$ | -0.0004 | 0.0001 | *** | -0.0003 | 0.0000 | *** |
| $export_{i,t-1}$ | 0.0023 | 0.0011 | ** | 0.0114 | 0.0015 | *** |
| $gturn_{i,t-1}$ | 0.0008 | 0.0001 | *** | 0.0041 | 0.0003 | *** |
| $tngassets_{i,t-1}$ | -0.0017 | 0.0017 | | -0.0020 | 0.0016 | |
| $risk_{i,t-1}$ | 0.0000 | 0.0000 | | 0.0040 | 0.0039 | |
| $cashflow_{i,t}$ | 0.0010 | 0.0001 | *** | 0.0026 | 0.0007 | *** |
| $turn_{i,t-1}$ | 0.0705 | 0.0417 | * | 0.0153 | 0.0022 | *** |
| $e1t9_{i,t-1}$ | - | - | - | - | - | - |
| $e10t49_{i,t-1}$ | 0.8212 | 1.2279 | | -1.5768 | 0.5236 | *** |
| $e50t249_{i,t-1}$ | 0.8084 | 2.2138 | | -1.4867 | 0.6288 | *** |
| $ege250_{i,t-1}$ | -2.2317 | 0.4271 | *** | -1.3069 | 1.1993 | |
| $age_{i,t}$ | -0.1537 | 0.0018 | *** | -0.0184 | 0.0082 | *** |
| $age^2_{i,t}$ | 0.0018 | 0.0002 | *** | 0.0021 | 0.0002 | *** |
| $agrc_{i,t}$ | - | - | - | - | - | - |
| $manf_{i,t}$ | -0.9626 | 0.0527 | *** | 0.4739 | 0.1578 | *** |
| $enrg_{i,t}$ | -1.3004 | 0.0435 | *** | -0.1102 | 0.4372 | |
| $cons_{i,t}$ | -6.3517 | 0.0634 | *** | -1.1031 | 0.6353 | * |
| $trad_{i,t}$ | -0.5996 | 0.0496 | | 0.7862 | 0.4962 | |
| $tran_{i,t}$ | -0.4845 | 0.1162 | *** | 3.5936 | 1.1599 | *** |
| $infr_{i,t}$ | 7.6173 | 0.0993 | *** | 2.1187 | 0.9961 | ** |
| $accm_{i,t}$ | -30.6544 | 0.2403 | *** | 2.8456 | 2.4049 | |
| $othr_{i,t}$ | 1.3699 | 0.0462 | *** | 0.1587 | 0.4645 | |
| $north_{i,t}$ | 3.6231 | 0.0938 | *** | 0.1570 | 0.9403 | |
| $centre_{i,t}$ | 11.2770 | 0.1025 | *** | 0.3637 | 0.0960 | *** |
| $lisbon_{i,t}$ | -3.2702 | 0.0903 | | 0.1936 | 0.1093 | * |
| $alentejo_{i,t}$ | 7.2386 | 0.1054 | *** | -0.3295 | 0.1530 | ** |
| $algarve_{i,t}$ | -9.5986 | 0.0944 | *** | 0.3687 | 0.1871 | ** |
| $azores_{i,t}$ | - | - | - | - | - | - |
| $madeira_{i,t}$ | -0.0566 | 0.1164 | | 0.1328 | 1.1675 | |

Table 3. (continuation)

| Dependent variable: *invrate$_{i,t}$* | Difference GMM (3) | | | System GMM (4) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| *2012$_i$* | - | - | - | - | - | - |
| *2013$_i$* | -0.0313 | 0.2791 | | 0.4129 | 0.7920 | |
| *2014$_i$* | 0.0112 | 0.3386 | | 1.3226 | 0.4040 | *** |
| *2015$_i$* | 0.0309 | 0.3179 | | 1.4170 | 0.2876 | *** |
| *2016$_i$* | 0.0788 | 0.3321 | | 1.2830 | 0.3878 | *** |
| *2017$_i$* | - | - | | 1.5123 | 0.2854 | *** |
| *2018$_i$* | 0.4722 | 0.5698 | | 2.0612 | 0.7785 | |
| *2019$_i$* | 0.4133 | 0.5551 | | 2.0424 | 0.4616 | *** |
| *constant* | - | - | - | 0.1063 | 1.0087 | |
| R-squared | - | | | - | | |
| Observations | 1,748,643 | | | 2,189,633 | | |
| m1 | -2.68 | | | -3.55 | | |
| m2 | 1.11 | | | 2.17 | | |
| Sargan | 0.427 | | | 0.152 | | |
| Instruments | Yes | | | Yes | | |

Source: Authors' calculations based on data from IBAS, Statistics Portugal.

Notes: Significance levels: ***, 1%; **, 5%; *, 10%. The dependent variable in the four models is the investment rate. The number of observations included in each model is the one presented in the table. The difference GMM estimator of Arellano and Bond was obtained at 2 steps, with strictly exogenous variables. The system GMM estimator was obtained at 1 step with strictly exogenous variables. m1 and m2 are test statistics referring to first and second order correlation, respectively. Sargan is a test for overidentification of GMM estimators' restrictions, where p-values are presented. Through the analysis of the Sargan test results, it is verified that the instruments used in the GMM estimators are valid and can be used in the estimation. The instruments used in the system GMM also do not reject the null hypothesis for a significance level of 2.5%.

Examining the remaining variables across both the pooled OLS and FE models, as well as in the difference GMM and system GMM, the estimation results partially align with other results in the literature. In particular, a significant portion of the coefficients demonstrated statistical significance (see Table 3). These findings are consistent with the observations made by Campa and Shaver (2002), Lang et al. (1996), Myers (1977), and Aivazian et al. (2005). These studies, highlighted in the literature review, provide valuable insights into the intricacies of investment determinants in diverse economic contexts.

Furthermore, a detailed examination of each explanatory variable within the various models reveals a nuanced perspective. The analysis focuses on the influence of indebtedness on investment, as measured by the higher weight of debt equity in the previous period ($debt_{i,t-1}$). The findings indicate that companies with higher levels of indebtedness exhibit a tendency toward lower investment. A negative coefficient implies an inverse relationship, showing that, on average, an increase in the weight of debt in total equity in the previous period is associated with a decrease in net investment. Specifically, considering the system GMM estimation result, a unit increase in the indebtedness ratio is associated with a decrease of 0.0003 units in the investment rate, ensuring that other variables constant.

This result is consistent with the broader understanding in the literature, including the works of Lang et al. (1996), Myers (1977), and Aivazian et al. (2005), which have consistently found that higher levels of indebtedness tend to be associated with lower levels of net investment. This indicates that firms with a relatively heavier debt burden may exhibit a more conservative approach to investment, possibly due to concerns related to financial leverage and risk.

The results also support the hypothesis that companies with a greater growth potential, or those aiming to compensate for potential shortfalls in installed production capacity, as measured by their export capacity (Campa & Shaver, 2002), present statistically significant results. This trend persists in various estimators, with a higher investment rate estimated for companies with a higher level of exports. In the context of the system GMM estimation, the positive coefficient implies that, on average, an increase of one unit in the level of exports is associated with an increase of 0.0114 units in investment. This indicates that firms with higher export capacity tend to have a higher proportion of investment.

The measure of growth potential, represented by sales growth, demonstrates statistical significance across different models. For the system GMM estimator, the positive coefficient of 0.0041 indicates that companies witnessing higher sales growth also tend to have increased investment. This finding aligns with expectations from the literature, including Lang et al. (1996), Campa and Shaver (2002), Aivazian et al. (2005), and Mofrad (2012), supporting the hypothesis that companies with substantial growth potential show higher levels of net investment. It should be mentioned that the estimate is statistically significant in all models, contrary to the findings in Mofrad (2012), where significance was only observed in the system GMM estimator. This consistency underlines the robustness of the relationship between sales growth and net investment in various estimation methodologies.

Concerning the impact of the proportion of tangible assets ($tngassets_{i,t-1}$) on investment decisions, the estimation results did not exhibit statistical significance. Despite this fact, it is relevant to note that all coefficients were consistently negative. This finding aligns with the conclusions of studies such as Lang et al. (1996) and McConnell and Servaes (1995), suggesting that firms with a higher proportion of tangible assets could face challenges in terms of investment decisions. However, it is crucial to acknowledge that this observation was not universally verified, as other studies, including Bond (2002), present varied results. The mixed evidence in the literature emphasises the complexity of the relationship between tangible assets and investment decisions.

Furthermore, the examination of the risk profile ($risk_{i,t-1}$) did not reveal significant implications for explaining investment, regardless of the estimator considered. This finding contrasts with some literature that emphasises the importance of considering risk profiles in understanding investment behaviours (Aivazian et al., 2005; Serrasqueiro et al., 2011). The results show evidence of a relationship between the ability to generate internal financial resources, measured by cash flow ($cashflow_{i,t}$), and the investment rate. This observation is consistent with the findings of Campa and Shaver (2002), which suggest that in the presence of liquidity constraints, companies with stable cash flows are more likely to exhibit a robust and consistent investment pattern. This outcome is also consistent with other studies, such as Williams (2007) and Martinez-Carrascal and Ferrando (2008), which show the importance of cash flow in determining investment decisions.

Examining the influence of the size of the company ($turn_{i,t-1}$) on the investment rate, measured by sales in millions of euros, the estimation results suggest a consistent positive relationship with the dependent variable in the four models considered. This indicates that the higher the company's sales, the higher the investment rate. The three dummy variables of the number of persons employed ($e10t49_{i,t-1}$, $e50t249_{i,t-1}$, and $ege250_{i,t-1}$), they exhibit a negative association with the dependent variable. This indicates a diminishing investment rate as the size of the enterprise increases, as consistently observed in the pooled OLS, FE, and system GMM models. These findings are consistent to direction across the pooled OLS, FE, and system GMM models, although the statistical significance varies. For instance, some estimates, such as those in the FE model, do not always reach the conventional levels of significance.

However, the results of the difference GMM suggest positive coefficients for the first two dummies ($e10t49_{i,t-1}$ and $e50t249_{i,t-1}$), implying an increase in the investment rate, and a negative coefficient for the last dummy ($ege250_{i,t-1}$), which is statistically significant. This difference highlights the importance of the selected estimation technique in interpreting the relationship between company size and investment dynamics. The nuanced nature of these results underscores the complexity of the size-related effects on investment, proving the need for careful consideration when selecting the appropriate econometric model.

Considering the impact of company age on investment reveals that this variable is statistically significant in the four estimated models. The coefficients consistently exhibit a negative trend, where the system GMM model indicates a coefficient of -0.0184. These findings imply that, on average, newer companies tend to invest more compared to their longer-established counterparts. This observation aligns with the notion that in the initial phases of their operations, companies often require significant investments in capital to establish and sustain their activities (Evans, 1987; Geroski, 1995; Bartelsman et al., 2013; Coad & Rao, 2008).

Regarding the quadratic effect of age (age squared), the coefficients maintained statistical significance, showcasing a consistent relationship across all estimated models, with a coefficient of 0.0021 in the system GMM. These results implies a non-linear relationship between net investment and age, indicating that both younger and older companies exhibit a higher investment rate, forming a U-shaped pattern. This pattern highlights the notion that companies, in their early and mature stages, demonstrate a greater propensity to invest, reflecting various operational needs and strategic considerations.

This finding aligns with the insights provided by Audretsch and Mahmood (1995). They explored the survival patterns of new companies, with a particular focus on the distinctive challenges and investment requirements encountered in the early stages of the existence of a company. Similarly, Baptista and Swann (1998) emphasised the impact of regional clusters on firms' innovation and growth trajectories, suggesting that geographical influences may contribute to the observed non-linear patterns. Furthermore, the work of Cefis and Marsili (2006) on the role of innovation in the survival of companies offers a valuable context, highlighting how innovative activities can influence investment decisions in different phases of the life cycle of a company. These insights collectively support the notion that younger and older companies, in their respective stages of development, may indeed demonstrate higher investment rates due to diverse operational needs and strategic considerations, contributing to the identified U-shaped pattern. In the next section, the consistency of the results by region is presented.

### 3.4.1 Consistency of the results by region

Recognising the heterogeneity in investment behaviours among companies operating in distinct regions or industries, the estimation of the model described in Equation (3.1) was carried out using the system GMM estimator. This choice is supported by the methodological considerations discussed in Section 3.3.1. The system GMM, with its capacity to address endogeneity concerns and enhance instrument validity, emerges as a robust estimator, particularly when dealing with persistent and closely related variables in the context of investment studies.

This research aims to determine whether there are nuanced patterns and different determinants of the investment rate by region. This section presents the results of the system GMM estimator considering the head office location within the seven NUTS 2 regions of Portugal. Based on the results obtained for each of these regions, as presented in Table 4, the general trends are largely in line with the results observed for the total sample of companies, regardless of their geographical locations.

Table 4. System GMM estimations for investment rate, by NUTS 2 regions

| Dependent variable: $invrate_{i,t}$ | NUTS 2 = North | | | NUTS 2 = Centre | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $invrate_{i,t-1}$ | 0.0770 | 0.0089 | *** | 0.0062 | 0.0001 | *** |
| $debt_{i,t-1}$ | -0.0004 | 0.0001 | *** | -0.0009 | 0.0003 | *** |
| $export_{i,t-1}$ | 0.0326 | 0.0120 | *** | 0.0701 | 0.0325 | ** |
| $gturn_{i,t-1}$ | 0.0047 | 0.0003 | *** | 0.0072 | 0.0007 | *** |
| $tngassets_{i,t-1}$ | -0.0007 | 0.0007 | | -0.1226 | 0.0500 | *** |
| $risk_{i,t-1}$ | 0.0047 | 0.0040 | | 0.0002 | 0.0001 | ** |
| $cashflow_{i,t}$ | 0.0021 | 0.0010 | ** | 0.0068 | 0.0075 | |
| $turn_{i,t-1}$ | 0.0149 | 0.0056 | *** | 0.0245 | 0.0070 | *** |
| $e1t9_{i,t-1}$ | - | - | | - | - | - |
| $e10t49_{i,t-1}$ | -2.1539 | 1.1464 | * | -1.7936 | 0.7806 | *** |
| $e50t249_{i,t-1}$ | -1.5120 | 0.5312 | *** | -3.2390 | 1.7478 | * |
| $ege250_{i,t-1}$ | -2.9557 | 1.1031 | *** | -6.1380 | 2.9815 | ** |
| $age_{i,t}$ | -0.0062 | 0.0019 | *** | -0.0259 | 0.0052 | *** |
| $age^2_{i,t}$ | 0.0023 | 0.0008 | *** | 0.0016 | 0.0008 | ** |
| $agrc_{i,t}$ | - | - | - | - | - | - |
| $manf_{i,t}$ | 1.5593 | 0.5175 | *** | -0.8540 | 1.3873 | |
| $enrg_{i,t}$ | 3.1926 | 1.1212 | *** | -2.0144 | 1.3244 | |
| $cons_{i,t}$ | 0.2838 | 0.1562 | * | 5.8785 | 4.9406 | |
| $trad_{i,t}$ | 1.0928 | 0.7225 | | 0.3600 | 0.3543 | |
| $tran_{i,t}$ | 1.2497 | 0.4748 | *** | -1.0491 | 0.9665 | |
| $infr_{i,t}$ | 0.1298 | 0.8162 | | 0.2215 | 0.4880 | |
| $accm_{i,t}$ | 9.6541 | 8.6233 | | -2.0098 | 1.2994 | |
| $othr_{i,t}$ | 4.6708 | 2.2850 | ** | 1.1659 | 2.4932 | |
| $2012_i$ | - | - | - | - | - | - |
| $2013_i$ | -0.2381 | 1.9865 | | 0.3697 | 0.3802 | |
| $2014_i$ | 0.3749 | 0.0371 | *** | 4.0379 | 0.3067 | *** |
| $2015_i$ | 2.1329 | 1.0584 | ** | 0.9671 | 0.0637 | *** |
| $2016_i$ | 1.8016 | 1.0297 | * | 1.3251 | 0.6659 | ** |
| $2017_i$ | 1.3555 | 0.6732 | ** | 2.1151 | 0.8071 | *** |
| $2018_i$ | 1.3813 | 0.0847 | *** | 4.9105 | 3.1306 | |
| $2019_i$ | 2.6241 | 0.8854 | *** | 2.0644 | 1.1081 | * |
| *constant* | -0.4849 | 0.4902 | | 3.6241 | 1.2434 | *** |
| R-squared | - | | | - | | |
| Observations | 643,82 | | | 397,641 | | |
| m1 | -1.91 | | | -5.20 | | |
| m2 | 0.38 | | | 1.31 | | |
| Sargan | 0.086 | | | 0.136 | | |
| Instruments | Yes | | | Yes | | |

Table 4. (continuation)

| Dependent variable: *invrate*$_{i,t}$ | NUTS 2 = Lisbon Metropolitan Area | | | NUTS 2 = Alentejo | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| *invrate*$_{i,t-1}$ | 0.0593 | 0.0031 | *** | 0.0022 | 0.0003 | *** |
| *debt*$_{i,t-1}$ | -0.0003 | 0.0000 | *** | -0.0003 | 0.0001 | *** |
| *export*$_{i,t-1}$ | 0.0260 | 0.0074 | *** | 0.0129 | 0.0011 | *** |
| *gturn*$_{i,t-1}$ | 0.0057 | 0.0004 | *** | 0.0003 | 0.0002 | * |
| *tngassets*$_{i,t-1}$ | -0.0285 | 0.0179 | | -0.0006 | 0.0006 | |
| *risk*$_{i,t-1}$ | 0.0035 | 0.0038 | | 0.0001 | 0.0001 | |
| *cashflow*$_{i,t}$ | 0.0128 | 0.0036 | *** | -0.0015 | 0.0015 | |
| *turn*$_{i,t-1}$ | 0.0199 | 0.0010 | *** | 0.0222 | 0.0045 | *** |
| *e1t9*$_{i,t-1}$ | - | - | - | - | - | - |
| *e10t49*$_{i,t-1}$ | -1.4195 | 0.4646 | *** | 3.2709 | 1.8431 | * |
| *e50t249*$_{i,t-1}$ | -1.5861 | 0.7043 | *** | 0.3588 | 1.7196 | |
| *ege250*$_{i,t-1}$ | -0.6428 | 0.2747 | *** | 1.2230 | 0.5765 | ** |
| *age*$_{i,t}$ | -0.0610 | 0.0022 | *** | 0.0289 | 0.0930 | |
| *age*$^2_{i,t}$ | 0.0030 | 0.0002 | *** | 0.0014 | 0.0008 | * |
| *agrc*$_{i,t}$ | - | - | - | - | - | - |
| *manf*$_{i,t}$ | 0.7885 | 1.2690 | | 1.1562 | 1.4621 | |
| *enrg*$_{i,t}$ | 0.6098 | 1.2608 | | -4.9002 | 4.7624 | |
| *cons*$_{i,t}$ | 0.8166 | 0.4075 | ** | -0.9543 | 0.7372 | |
| *trad*$_{i,t}$ | 1.7816 | 1.1894 | | -1.4660 | 1.1646 | |
| *tran*$_{i,t}$ | 1.9831 | 0.5282 | *** | -1.3406 | 0.8886 | |
| *infr*$_{i,t}$ | 0.8410 | 1.3173 | | 0.0977 | 0.7800 | |
| *accm*$_{i,t}$ | 0.5858 | 0.0757 | *** | -0.7147 | 1.0106 | |
| *othr*$_{i,t}$ | 1.2721 | 0.2649 | *** | 2.9459 | 1.6256 | * |
| *2012*$_{i}$ | - | - | - | - | - | - |
| *2013*$_{i}$ | 1.2128 | 0.9602 | | -2.3037 | 3.1954 | |
| *2014*$_{i}$ | 0.1364 | 0.4927 | | 1.7567 | 3.4749 | |
| *2015*$_{i}$ | 1.5382 | 0.9004 | * | -0.3187 | 1.0240 | |
| *2016*$_{i}$ | 0.3945 | 0.1736 | *** | -0.6470 | 0.8134 | |
| *2017*$_{i}$ | 1.3305 | 0.2211 | *** | 0.8969 | 1.3920 | |
| *2018*$_{i}$ | 1.2451 | 0.5116 | *** | 0.2072 | 0.7960 | |
| *2019*$_{i}$ | 1.7129 | 0.7040 | *** | -0.8053 | 0.6942 | |
| *constant* | 3.3029 | 1.4695 | *** | 0.8669 | 1.5869 | |
| R-squared | - | | | - | | |
| Observations | 531,871 | | | 117,479 | | |
| m1 | -2.71 | | | -2.44 | | |
| m2 | 1.94 | | | -0.95 | | |
| Sargan | 0.032 | | | 0.000 | | |
| Instruments | Yes | | | Yes | | |

Table 4. (continuation)

| Dependent variable: $invrate_{i,t}$ | NUTS 2 = Algarve | | | NUTS 2 = Autonomous Region of the Azores | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $invrate_{i,t-1}$ | 0.0107 | 0.0052 | ** | 0.0024 | 0.0002 | *** |
| $debt_{i,t-1}$ | -0.0070 | 0.0005 | *** | 0.0021 | 0.0011 | ** |
| $export_{i,t-1}$ | 0.0190 | 0.0074 | *** | 0.0009 | 0.0011 | |
| $gturn_{i,t-1}$ | 0.0004 | 0.0007 | | 0.0005 | 0.0002 | ** |
| $tngassets_{i,t-1}$ | -0.1273 | 0.0295 | *** | -0.0702 | 0.0340 | ** |
| $risk_{i,t-1}$ | 0.0001 | 0.0004 | | 0.0001 | 0.0001 | |
| $cashflow_{i,t}$ | 0.0007 | 0.0004 | * | 0.0001 | 0.0000 | * |
| $turn_{i,t-1}$ | 0.0512 | 0.0075 | *** | 0.0096 | 0.0046 | ** |
| $e1t9_{i,t-1}$ | - | - | - | - | - | - |
| $e10t49_{i,t-1}$ | -1.2754 | 0.3705 | *** | -1.0873 | 1.5983 | |
| $e50t249_{i,t-1}$ | -0.5198 | 0.4720 | | -0.7332 | 1.3218 | |
| $ege250_{i,t-1}$ | 0.4962 | 2.1400 | | -4.0612 | 5.0369 | |
| $age_{i,t}$ | 0.0100 | 0.0465 | | 0.0743 | 0.1546 | |
| $age^2_{i,t}$ | -0.0006 | 0.0008 | | -0.0014 | 0.0021 | |
| $agrc_{i,t}$ | - | - | - | - | - | - |
| $manf_{i,t}$ | -6.0550 | 3.4689 | * | -0.8280 | 0.5987 | |
| $enrg_{i,t}$ | -4.9304 | 3.4169 | | -0.3754 | 0.3193 | |
| $cons_{i,t}$ | -2.9409 | 3.2705 | | -0.0792 | 1.5480 | |
| $trad_{i,t}$ | -3.2592 | 3.2387 | | 4.8661 | 1.8051 | *** |
| $tran_{i,t}$ | -5.0526 | 3.3579 | | -0.1163 | 0.2597 | |
| $infr_{i,t}$ | -3.1612 | 3.2948 | | 0.9354 | 0.6376 | |
| $accm_{i,t}$ | 5.4389 | 2.7333 | ** | -0.1561 | 0.5195 | |
| $othr_{i,t}$ | 3.2131 | 1.2749 | *** | 8.0579 | 4.5676 | * |
| $2012_i$ | - | - | - | - | - | - |
| $2013_i$ | 1.9368 | 1.5824 | | 0.4303 | 0.2155 | ** |
| $2014_i$ | 0.0448 | 0.2142 | | 0.1076 | 0.0667 | |
| $2015_i$ | 0.3820 | 0.2721 | | 0.4222 | 0.1335 | *** |
| $2016_i$ | 2.1556 | 0.8612 | *** | 9.9169 | 1.8201 | *** |
| $2017_i$ | 1.1658 | 0.3868 | *** | 0.1065 | 0.1111 | |
| $2018_i$ | 1.2884 | 0.5998 | ** | -0.4983 | 0.7457 | |
| $2019_i$ | 3.2484 | 2.1662 | | 0.2867 | 0.0457 | *** |
| *constant* | 8.6984 | 3.4554 | *** | 1.4848 | 1.0098 | |
| R-squared | - | | | - | | |
| Observations | 84,142 | | | 25,804 | | |
| m1 | -2.73 | | | -2.14 | | |
| m2 | -0.84 | | | -2.13 | | |
| Sargan | 0.065 | | | 0.066 | | |
| Instruments | Yes | | | Yes | | |

Table 4. (continuation)

| Dependent variable: $invrate_{i,t}$ | NUTS 2 = Autonomous Region of Madeira | | |
|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $invrate_{i,t-1}$ | 0.0131 | 0.0023 | *** |
| $debt_{i,t-1}$ | -0.0003 | 0.0001 | *** |
| $export_{i,t-1}$ | 0.0505 | 0.0245 | ** |
| $gturn_{i,t-1}$ | 0.0007 | 0.0009 | |
| $tngassets_{i,t-1}$ | -0.0972 | 0.0602 | |
| $risk_{i,t-1}$ | 0.0023 | 0.0019 | |
| $cashflow_{i,t}$ | 0.0016 | 0.0010 | * |
| $turn_{i,t-1}$ | 0.1770 | 0.0435 | *** |
| $e1t9_{i,t-1}$ | - | - | - |
| $e10t49_{i,t-1}$ | -2.0505 | 1.4243 | |
| $e50t249_{i,t-1}$ | -1.9918 | 1.3183 | |
| $ege250_{i,t-1}$ | -10.8651 | 9.8431 | |
| $age_{i,t}$ | 0.0289 | 0.0436 | |
| $age^2_{i,t}$ | -0.0006 | 0.0007 | |
| $agrc_{i,t}$ | - | - | - |
| $manf_{i,t}$ | -3.3909 | 2.1301 | |
| $enrg_{i,t}$ | -1.9390 | 2.1582 | |
| $cons_{i,t}$ | -1.7258 | 1.4731 | |
| $trad_{i,t}$ | -3.4678 | 2.2027 | |
| $tran_{i,t}$ | -3.0088 | 1.7521 | * |
| $infr_{i,t}$ | -1.2103 | 1.6940 | |
| $accm_{i,t}$ | -7.7487 | 4.4487 | * |
| $othr_{i,t}$ | 5.0415 | 7.6747 | |
| $2012_i$ | - | - | - |
| $2013_i$ | 1.5989 | 1.0926 | |
| $2014_i$ | 4.5975 | 0.9807 | *** |
| $2015_i$ | -1.3656 | 0.4314 | *** |
| $2016_i$ | -0.0890 | 1.1973 | |
| $2017_i$ | 1.6178 | 0.3181 | *** |
| $2018_i$ | 1.8191 | 0.3021 | *** |
| $2019_i$ | 1.8431 | 0.4160 | *** |
| *constant* | 5.3052 | 3.0721 | * |
| R-squared | - | | |
| Observations | 38,1 | | |
| m1 | -2.83 | | |
| m2 | -0.65 | | |
| Sargan | 0.003 | | |
| Instruments | Yes | | |

Table 4. (continuation)

Source: Authors' calculations based on data from IBAS, Statistics Portugal.

Notes: Significance levels: ***, 1%; **, 5%; *, 10%. The dependent variable in the models is the investment rate. The number of observations included in each model is the one presented in the table. The system GMM estimator was obtained at 1 step with strictly exogenous variables. m1 and m2 are test statistics referring to first and second order correlation, respectively. Sargan is a test for overidentification of the system GMM estimator restrictions, where p-values are presented. Through the analysis of the Sargan test results, it is verified that the instruments used in the GMM estimator are valid and can be used in the estimation. The instruments used in the system GMM also do not reject the null hypothesis for a significance level of 2.5%.

Regarding the coefficient of the autoregressive element between regions, a consistent positive and statistically significant relationship was identified. Notably, the strength of this association varied, ranging from 0.0022 in the Alentejo region to 0.0770 in the North region, mirroring the trend observed in the overall results. This again confirms the persistence of the autoregressive effect on net investment, emphasising its role in different regional contexts.

Regarding the level of indebtedness, the results reveal a distinctive trend among companies located in the Autonomous Region of the Azores, separating them from the general trend observed across the entire sample of companies. In this region, a higher previous period indebtedness seems to correspond to a higher investment rate. This deviation from the broader pattern suggests potential regional-specific dynamics that require further exploration, diverging from the findings presented by Lang et al. (1996), Myers (1977) and Aivazian et al. (2005).

Considering the impact of exports on investment, most regions, excluding the Autonomous Region of the Azores, exhibited statistically significant results. The Centre region stands out with the highest coefficient (0.0701), reinforcing the positive relationship between export capacity and investment (Campa & Shaver, 2002). This trend aligns with the overall results, emphasising the general importance of export orientation in influencing investment decisions.

The influence of sales growth on investment shows consistency across several regions, especially in the Centre, Lisbon Metropolitan Area, and the North regions, where coefficients are 0.0047 or higher. The results in the Algarve and Autonomous Region of Madeira do not reach statistical significance. This regional variation echoes the global findings, highlighting the nuanced impact of sales growth on investment across different geographical contexts (Lang et al., 1996; Campa & Shaver, 2002; Aivazian et al., 2005; Mofrad, 2012).

The risk profile and internal financial resources (cash flow) do not emerge as significant factors in explaining net investment in any region. This result contrasts with certain literature that underscores their importance (Aivazian et al., 2005; Serrasqueiro et al., 2011), indicating potential regional-specific dynamics shaping investment decisions.

The tangibility of assets proves to be influential in explaining investment in companies located in the Centre, Algarve and Autonomous Region of the Azores, aligning with broader trends observed in the overall sample. Despite the global results not reaching significance, these regional patterns are consistent with Lang et al. (1996) and McConnell and Servaes (1995), suggesting that firms with a higher proportion of tangible assets face challenges in making investment decisions.

The risk profile reveals significant implications for explaining investment in companies only in the Centre region. This finding aligns with those of Aivazian et al. (2005) and Serrasqueiro et al. (2011). This regional variation underscores the contextual importance of risk considerations in investment behaviours. In the Centre region, the relationship between risk and investment is particularly pronounced, indicating that companies in this area may be more sensitive to risk factors when making investment decisions.

Sales amounts emerge as a statistically significant factor in explaining investment in companies across all regions, as verified in the overall results. This finding indicates the regional relevance of sales amounts as a determinant of investment. The positive relationship between sales and investment rate indicates that higher sales volumes provide companies with the necessary resources and confidence to invest more. This relationship has been verified by Lang et al. (1996), Campa and Shaver (2002), Aivazian et al. (2005), and Mofrad (2012). These studies highlight how sales performance can drive investment decisions by improving liquidity and reducing perceived financial risks.

Regarding age and age squared, their significance is observed in three of the seven regions, namely in the North, Centre and Lisbon Metropolitan Area, reflecting the global results. In Alentejo, only age squared exhibits statistical significance. This regional variation aligns with the identified U-shaped pattern in the relationship between investment and company age, reinforcing the need for region-specific interpretations (Audretsch & Mahmood, 1995; Baptista & Swann, 1998; Cefis & Marsili, 2006).

### 3.4.2 Consistency of the results by industry

The general results obtained for each of the nine industries, presented in Table 5, confirm the findings observed for the total sample of companies, emphasising the consistency of certain trends in different industries. However, when comparing the detailed results for each economic activity with those for all companies, several important insights can be observed.

The coefficient of the autoregressive element remains consistently positive and statistically significant in all economic activities. In particular, other services, accommodation and food services, distributive trade, and energy and water exhibit higher coefficients compared to the total sample, emphasising the general impact of the autoregressive effect on net investment (Bond et al., 2001).

The results related to the company's indebtedness in the previous year differ between economic industries. Distributive trade, transportation and storage, and other services show positive coefficients, indicating that higher indebtedness corresponds to a higher investment rate. In contrast, the manufacturing industry, although it contributes significantly to net investment, shows a negative relationship between indebtedness and investment, which is consistent with the general findings (Lang et al., 1996; Myers, 1977; Aivazian et al., 2005).

The impact of growth potential, measured by export capacity, is consistent across economic activities, with manufacturing, accommodation and food services exhibiting the highest coefficients (0.0162 and 0.0148, respectively). This aligns with the global results, highlighting the industry-specific nuances in the relationship between export capacity and investment (Campa & Shaver, 2002).

The coefficients related to sales growth were positive and statistically significant in all economic activities, reflecting global findings. This underscores the universal influence of sales growth on net investment in various industries (Lang et al., 1996; Campa & Shaver, 2002; Aivazian et al., 2005; Mofrad, 2012).

The tangibility of assets has a consistent negative influence on investment in specific industries, including manufacturing, energy and water, construction and real estate, distributive trade, and transportation and storage. Although the overall results do not reach significance, these industry patterns suggest challenges faced by companies with a higher proportion of tangible assets in making investment decisions, reflecting broader trends observed in the literature (Lang et al., 1996; McConnell & Servaes, 1995).

The risk profile of companies does not emerge as a significant factor in explaining net investment in any of the economic activities, which is consistent with the general findings. The ability to generate internal financial resources (cash flow) is statistically significant in all economic activities. However, accommodation and food services and

Table 5. System GMM estimations for investment rate, by industry

| Dependent variable: $invrate_{i,t}$ | Agriculture and fishing | | | Manufacturing | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $invrate_{i,t-1}$ | 0.0020 | 0.0002 | *** | 0.0366 | 0.0068 | *** |
| $debt_{i,t-1}$ | -0.0002 | 0.0001 | * | -0.0014 | 0.0003 | *** |
| $export_{i,t-1}$ | 0.0055 | 0.0007 | *** | 0.0162 | 0.0019 | *** |
| $gturn_{i,t-1}$ | 0.0012 | 0.0001 | *** | 0.0024 | 0.0002 | *** |
| $tngassets_{i,t-1}$ | -0.0004 | 0.0004 | | -0.0476 | 0.0270 | * |
| $risk_{i,t-1}$ | 0.0011 | 0.0021 | | -0.0024 | 0.0024 | |
| $cashflow_{i,t}$ | 0.0382 | 0.0025 | *** | 0.0103 | 0.0010 | *** |
| $turn_{i,t-1}$ | 0.0576 | 0.0044 | *** | 0.0566 | 0.0051 | *** |
| $e1t9_{i,t-1}$ | - | - | - | - | - | - |
| $e10t49_{i,t-1}$ | -0.7644 | 0.2793 | *** | -0.8017 | 0.3570 | *** |
| $e50t249_{i,t-1}$ | -1.3957 | 0.5078 | *** | -0.9179 | 0.3516 | *** |
| $ege250_{i,t-1}$ | -3.2247 | 1.7410 | * | -1.2915 | 0.5247 | *** |
| $age_{i,t}$ | -0.0429 | 0.0259 | * | -0.1342 | 0.0639 | ** |
| $age^2_{i,t}$ | 0.0002 | 0.0003 | | 0.0012 | 0.0005 | *** |
| $north_{i,t}$ | 0.1223 | 0.0478 | *** | 0.2651 | 0.1004 | *** |
| $centre_{i,t}$ | 0.1078 | 0.0403 | *** | 0.2975 | 0.1373 | ** |
| $lisbon_{i,t}$ | 1.9900 | 0.6066 | *** | 3.2998 | 0.5246 | *** |
| $alentejo_{i,t}$ | 1.0629 | 0.3728 | *** | -0.0349 | 0.2591 | |
| $algarve_{i,t}$ | 3.6983 | 1.5955 | *** | 0.0201 | 0.0879 | |
| $azores_{i,t}$ | - | - | - | - | - | - |
| $madeira_{i,t}$ | 1.9379 | 1.4552 | | -0.5283 | 0.2696 | * |
| $2012_i$ | - | - | - | - | - | - |
| $2013_i$ | 1.8367 | 0.6957 | *** | 2.2630 | 1.0265 | ** |
| $2014_i$ | -0.0060 | 0.0652 | | 1.1160 | 0.5479 | ** |
| $2015_i$ | 0.1351 | 0.0817 | * | 1.6340 | 0.7647 | ** |
| $2016_i$ | 0.3766 | 0.1764 | ** | 0.3253 | 0.1053 | *** |
| $2017_i$ | 2.0504 | 0.9202 | ** | 0.7381 | 0.3778 | * |
| $2018_i$ | 0.2055 | 0.0730 | *** | 0.3846 | 0.2238 | * |
| $2019_i$ | 0.8963 | 0.4039 | ** | 1.1332 | 0.5216 | ** |
| *constant* | 0.2810 | 0.3005 | | 3.2444 | 1.2539 | *** |
| R-squared | - | | | - | | |
| Observations | 70,961 | | | 234,075 | | |
| m1 | -7.97 | | | -2.77 | | |
| m2 | 0.55 | | | 0.16 | | |
| Sargan | 0.238 | | | 0.104 | | |
| Instruments | Yes | | | Yes | | |

Table 5. (continuation)

| Dependent variable: $invrate_{i,t}$ | Energy and water | | | Construction and real estate | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $invrate_{i,t-1}$ | 0.0622 | 0.0029 | *** | 0.0198 | 0.0024 | *** |
| $debt_{i,t-1}$ | -0.0005 | 0.0000 | *** | -0.0148 | 0.0024 | *** |
| $export_{i,t-1}$ | 0.0067 | 0.0095 | | 0.0089 | 0.0063 | |
| $gturn_{i,t-1}$ | 0.0022 | 0.0002 | *** | 0.0238 | 0.0029 | *** |
| $tngassets_{i,t-1}$ | -0.0673 | 0.0299 | *** | -0.0932 | 0.0366 | *** |
| $risk_{i,t-1}$ | 0.0025 | 0.0070 | | 0.0006 | 0.0010 | |
| $cashflow_{i,t}$ | 0.0031 | 0.0014 | ** | 0.0060 | 0.0008 | *** |
| $turn_{i,t-1}$ | 0.0012 | 0.0004 | *** | 0.0243 | 0.0028 | *** |
| $e1t9_{i,t-1}$ | - | - | - | - | - | - |
| $e10t49_{i,t-1}$ | -1.1331 | 0.7880 | | -0.0335 | 1.7261 | |
| $e50t249_{i,t-1}$ | -1.1593 | 0.6667 | * | -2.9874 | 2.5372 | |
| $ege250_{i,t-1}$ | -1.1438 | 0.6009 | * | -21.7086 | 21.4216 | |
| $age_{i,t}$ | -0.0239 | 0.0485 | | -0.1077 | 0.0262 | *** |
| $age^2_{i,t}$ | 0.0003 | 0.0005 | | 0.0026 | 0.0008 | *** |
| $north_{i,t}$ | -3.1647 | 1.6643 | * | 2.1241 | 0.9014 | *** |
| $centre_{i,t}$ | -4.0791 | 2.4795 | * | -0.2984 | 0.4793 | |
| $lisbon_{i,t}$ | -4.4612 | 2.4953 | * | 1.2580 | 0.5836 | ** |
| $alentejo_{i,t}$ | -4.3662 | 2.5181 | * | -4.1613 | 4.3161 | |
| $algarve_{i,t}$ | -3.6670 | 1.6764 | ** | 0.7083 | 0.2752 | *** |
| $azores_{i,t}$ | - | - | - | - | - | - |
| $madeira_{i,t}$ | -4.6249 | 2.5464 | * | 0.3103 | 0.6724 | |
| $2012_i$ | - | - | - | - | - | - |
| $2013_i$ | 0.3056 | 0.1954 | | -0.8331 | 0.8029 | |
| $2014_i$ | -0.4347 | 0.2168 | ** | 0.7284 | 0.5534 | |
| $2015_i$ | -0.4661 | 0.2299 | ** | 2.0359 | 1.1079 | * |
| $2016_i$ | 1.4575 | 0.8747 | * | 4.8720 | 2.4878 | * |
| $2017_i$ | 0.6972 | 0.5636 | | 4.6913 | 1.9683 | *** |
| $2018_i$ | 0.0905 | 0.2667 | | 4.3245 | 2.4109 | * |
| $2019_i$ | -0.3198 | 0.1351 | *** | 2.1887 | 1.0216 | ** |
| *constant* | 7.8714 | 3.0470 | *** | 2.2708 | 1.1322 | ** |
| R-squared | - | | | - | | |
| Observations | 8,942 | | | 246,809 | | |
| m1 | -1.43 | | | -3.74 | | |
| m2 | 1.22 | | | 0.05 | | |
| Sargan | 0.001 | | | 0.316 | | |
| Instruments | Yes | | | Yes | | |

Table 5. (continuation)

| Dependent variable: $invrate_{i,t}$ | Distributive trade | | | Transportation and storage | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $invrate_{i,t-1}$ | 0.0646 | 0.0087 | *** | 0.0371 | 0.0106 | *** |
| $debt_{i,t-1}$ | 0.0141 | 0.0010 | *** | 0.0001 | 0.0000 | *** |
| $export_{i,t-1}$ | 0.0605 | 0.0056 | *** | 0.0093 | 0.0211 | |
| $gturn_{i,t-1}$ | 0.0022 | 0.0003 | *** | 0.0072 | 0.0005 | *** |
| $tngassets_{i,t-1}$ | -0.0915 | 0.0253 | *** | -0.2928 | 0.0456 | *** |
| $risk_{i,t-1}$ | -0.0016 | 0.0022 | | -0.0146 | 0.0221 | |
| $cashflow_{i,t}$ | 0.0008 | 0.0002 | *** | 0.0064 | 0.0003 | *** |
| $turn_{i,t-1}$ | 0.0025 | 0.0029 | | 0.0048 | 0.0043 | |
| $e1t9_{i,t-1}$ | - | - | - | - | - | - |
| $e10t49_{i,t-1}$ | -0.4060 | 0.1987 | ** | -3.4015 | 2.0671 | * |
| $e50t249_{i,t-1}$ | -2.2320 | 1.1096 | ** | -3.9198 | 2.0121 | * |
| $ege250_{i,t-1}$ | -1.9914 | 0.9963 | ** | -3.5129 | 2.2896 | |
| $age_{i,t}$ | -0.1504 | 0.0331 | *** | 0.2466 | 0.0770 | *** |
| $age^2_{i,t}$ | 0.0036 | 0.0011 | *** | -0.0024 | 0.0008 | *** |
| $north_{i,t}$ | 0.5451 | 0.6591 | | -5.1190 | 18.2363 | |
| $centre_{i,t}$ | 1.2621 | 0.9666 | | -5.4749 | 18.1772 | |
| $lisbon_{i,t}$ | 0.3447 | 0.4599 | | -6.1613 | 18.0768 | |
| $alentejo_{i,t}$ | 1.6005 | 1.3709 | | -5.4215 | 18.0649 | |
| $algarve_{i,t}$ | 0.1133 | 0.3035 | | -3.7746 | 18.8242 | |
| $azores_{i,t}$ | - | - | - | - | - | - |
| $madeira_{i,t}$ | 0.1988 | 0.3771 | | -6.0377 | 17.9570 | |
| $2012_i$ | - | - | - | - | - | - |
| $2013_i$ | -0.0801 | 0.1337 | | 0.6076 | 0.4918 | |
| $2014_i$ | 3.4005 | 1.2152 | *** | -1.5297 | 0.5313 | *** |
| $2015_i$ | 1.3386 | 0.8101 | * | 4.9424 | 2.7917 | * |
| $2016_i$ | -0.0827 | 0.2733 | | 4.5413 | 1.5136 | *** |
| $2017_i$ | 0.2001 | 0.1520 | | 0.8402 | 0.5192 | |
| $2018_i$ | 1.3221 | 0.5221 | *** | 0.9354 | 0.4641 | ** |
| $2019_i$ | 2.6155 | 1.1569 | *** | 6.2512 | 2.3146 | *** |
| *constant* | 3.0793 | 0.8916 | *** | 24.1041 | 17.7767 | |
| R-squared | - | | | - | | |
| Observations | 502,766 | | | 94,704 | | |
| m1 | -3.05 | | | -2.20 | | |
| m2 | 1.70 | | | 0.73 | | |
| Sargan | 0.011 | | | 0.142 | | |
| Instruments | Yes | | | Yes | | |

Table 5. (continuation)

| Dependent variable: $invrate_{i,t}$ | Information and communication | | | Accommodation and food services | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $invrate_{i,t-1}$ | 0.0396 | 0.0044 | *** | 0.0732 | 0.0087 | *** |
| $debt_{i,t-1}$ | -0.0037 | 0.0007 | *** | -0.0001 | 0.0000 | *** |
| $export_{i,t-1}$ | 0.0037 | 0.0012 | *** | 0.0148 | 0.0021 | *** |
| $gturn_{i,t-1}$ | 0.0075 | 0.0009 | *** | 0.0437 | 0.0039 | *** |
| $tngassets_{i,t-1}$ | -0.0147 | 0.0136 | | -0.0968 | 0.0674 | |
| $risk_{i,t-1}$ | -0.0040 | 0.0048 | | -0.0283 | 0.0839 | |
| $cashflow_{i,t}$ | 0.0007 | 0.0001 | *** | -0.0039 | 0.0007 | *** |
| $turn_{i,t-1}$ | 0.0826 | 0.0110 | *** | 0.0010 | 0.0003 | *** |
| $e1t9_{i,t-1}$ | - | - | - | - | - | - |
| $e10t49_{i,t-1}$ | -1.2404 | 0.8503 | | -3.7301 | 3.0059 | |
| $e50t249_{i,t-1}$ | -1.5154 | 0.9057 | * | -4.1624 | 2.7454 | |
| $ege250_{i,t-1}$ | -1.4916 | 0.8819 | * | -2.4705 | 4.4339 | |
| $age_{i,t}$ | 0.1564 | 0.0584 | *** | 0.2463 | 0.1161 | ** |
| $age^2_{i,t}$ | -0.0018 | 0.0007 | *** | -0.0047 | 0.0051 | |
| $north_{i,t}$ | 1.1591 | 0.6600 | * | 3.6047 | 0.9103 | *** |
| $centre_{i,t}$ | 5.6842 | 2.3513 | *** | -0.1089 | 0.3514 | |
| $lisbon_{i,t}$ | 1.1508 | 0.7286 | | 1.4669 | 0.4891 | *** |
| $alentejo_{i,t}$ | 0.8925 | 0.6532 | | -1.1724 | 0.4695 | *** |
| $algarve_{i,t}$ | 1.8714 | 0.7540 | *** | 0.2648 | 0.1326 | ** |
| $azores_{i,t}$ | - | - | - | - | - | - |
| $madeira_{i,t}$ | 1.3124 | 1.3482 | | 4.9611 | 2.0189 | *** |
| $2012_i$ | - | - | - | - | - | - |
| $2013_i$ | 0.7361 | 0.3857 | * | 5.9684 | 3.6281 | * |
| $2014_i$ | 0.4734 | 0.3261 | | 0.3758 | 0.2393 | |
| $2015_i$ | 0.5968 | 0.3528 | * | -0.5565 | 0.3061 | * |
| $2016_i$ | 1.7715 | 1.0474 | * | -0.2660 | 0.2625 | |
| $2017_i$ | 3.0507 | 0.9954 | *** | 0.7202 | 0.3694 | * |
| $2018_i$ | 5.8466 | 2.5261 | *** | 2.4343 | 1.0798 | *** |
| $2019_i$ | -0.0806 | 0.6332 | | 2.4896 | 1.4865 | * |
| *constant* | -2.8965 | 2.2554 | | -1.1061 | 4.3520 | |
| R-squared | - | | | - | | |
| Observations | 179,797 | | | 41,436 | | |
| m1 | -3.80 | | | -1.66 | | |
| m2 | -1.17 | | | 0.90 | | |
| Sargan | 0.157 | | | 0.000 | | |
| Instruments | Yes | | | Yes | | |

Table 5. (continuation)

| Dependent variable: *$invrate_{i,t}$* | Other services | | |
|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $invrate_{i,t-1}$ | 0.0856 | 0.0240 | *** |
| $debt_{i,t-1}$ | 0.0050 | 0.0006 | *** |
| $export_{i,t-1}$ | 0.0095 | 0.0070 | |
| $gturn_{i,t-1}$ | 0.0760 | 0.0082 | *** |
| $tngassets_{i,t-1}$ | -0.0006 | 0.0005 | |
| $risk_{i,t-1}$ | 0.0253 | 0.0208 | |
| $cashflow_{i,t}$ | -0.0040 | 0.0004 | *** |
| $turn_{i,t-1}$ | 0.0903 | 0.0502 | * |
| $e1t9_{i,t-1}$ | - | - | - |
| $e10t49_{i,t-1}$ | -3.7577 | 2.5298 | |
| $e50t249_{i,t-1}$ | 0.0910 | 0.7775 | |
| $ege250_{i,t-1}$ | 6.3660 | 4.8001 | |
| $age_{i,t}$ | -0.0362 | 0.0114 | *** |
| $age^2_{i,t}$ | 0.0016 | 0.0007 | *** |
| $north_{i,t}$ | 0.7978 | 0.2571 | *** |
| $centre_{i,t}$ | 0.2644 | 0.1212 | ** |
| $lisbon_{i,t}$ | 0.4022 | 0.1768 | *** |
| $alentejo_{i,t}$ | 0.0973 | 0.7268 | |
| $algarve_{i,t}$ | 0.8134 | 0.2215 | *** |
| $azores_{i,t}$ | - | - | - |
| $madeira_{i,t}$ | 0.5834 | 1.0734 | |
| $2012_i$ | - | - | - |
| $2013_i$ | -1.8297 | 0.9326 | ** |
| $2014_i$ | 0.3678 | 0.2047 | * |
| $2015_i$ | 1.2409 | 0.6627 | * |
| $2016_i$ | 1.2688 | 0.5552 | *** |
| $2017_i$ | 2.1735 | 1.0716 | ** |
| $2018_i$ | 1.1628 | 0.4891 | *** |
| $2019_i$ | 2.2101 | 0.8250 | *** |
| *constant* | 1.3884 | 0.7860 | * |
| R-squared | - | | |
| Observations | 454,131 | | |
| m1 | -2.23 | | |
| m2 | 1.79 | | |
| Sargan | 0.034 | | |
| Instruments | Yes | | |

Table 5. (continuation)

Source: Authors' calculations based on data from IBAS, Statistics Portugal.

Notes: Significance levels: ***, 1%; **, 5%; *, 10%. The dependent variable in all models is investment rate. The number of observations included in each model is the one presented in the table. The system GMM estimator was obtained at 1 step with strictly exogenous variables. m1 and m2 are test statistics referring to first and second order correlation, respectively. Sargan is a test for overidentification of the system GMM estimator restrictions, where p-values are presented. Through the analysis of the Sargan test results, it is verified that the instruments used in the GMM estimator are valid and can be used in the estimation. The instruments used in the system GMM also do not reject the null hypothesis for a significance level of 2.5%.

other services display negative coefficients, suggesting an inverse relationship between cash flows and investment rates in these industries, contrary to the other industries and the total sample (Campa & Shaver, 2002; Williams, 2007; Martinez-Carrascal & Ferrando, 2008).

Sales amounts are not statistically significant in explaining the net investment for companies in distributive trade and transportation and storage. However, the remaining economic activities show statistically significant coefficients, aligned with the global results and emphasising the industry-specific relevance of sales amounts as a determinant of investment (Lang et al., 1996; Campa & Shaver, 2002; Aivazian et al., 2005; Mofrad, 2012).

Concerning the effect of company size levels on investment, particularly in terms of aggregations of persons employed, the other services industries stand out. Although not statistically significant, companies with 50 to 249 persons employed and 250 or more persons employed exhibit positive coefficients, indicating potential variations in the relationship between company size and investment in this industry.

With regard to age variables, most economic industries align with the general patterns. However, the transportation and storage, and information and communication industries deviate, showing a positive coefficient for the age of the company and a negative coefficient for age squared. Accommodation and food services also display a positive relationship between the age of the company and the investment rate, highlighting industry-specific variations in the relationship between the age of the company and the investment rates (Audretsch & Mahmood, 1995; Baptista & Swann, 1998; Cefis & Marsili, 2006).

## 3.5 Conclusions and remarks

This chapter explored the evolution of company investment from 2010 to 2019, with a specific focus on regional, industrial, and size-related variations. The total net investment of Portuguese companies reached its maximum value of €21.4 billion in 2019, reflecting a substantial growth of 12.7% compared to 2010, having reached its lowest value in 2012, around €10.4 billion, and began to recover in the following years.

Subsequently, an econometric analysis was conducted to identify the factors that influence net investment by Portuguese companies.  The empirical results generated key insights into the complex dynamics that shape companies' investment decisions within the specified time frame. This study used various estimation methods, and the choice among them was based on the considerations described in the literature. In particular, the system GMM estimator is recommended for its better efficiency in dynamic panel data models and its ability to overcome weak instrument problems.

The empirical results of the research confirm the second rule of thumb proposed by Bond et al. (2001), suggesting the superiority of the system GMM estimator over the difference GMM estimator in cases where the dependent variable is persistent. This is crucial to estimate the autoregressive element related to the investment rate in the previous period.

It was observed that there is a negative correlation between indebtedness levels and net investment, thus corroborating the findings of Lang et al. (1996), Myers (1977), and Aivazian et al. (2005). Companies with heavier debt burdens exhibit a more conservative approach to investment, potentially due to concerns related to financial leverage and risk. This cautious behaviour likely stems from the need to manage financial stability, particularly in uncertain economic climates. As such, heavily indebted companies may prioritise debt servicing over new investments, affecting their long-term growth potential.

Companies with higher potential growth, measured by export capacity and sales growth, show higher net investment levels. This aligns with expectations from the literature (Campa & Shaver, 2002; Lang et al., 1996; Aivazian et al., 2005), emphasising the positive relationship between growth indicators and investment. The high growth potential provides companies with the necessary resources and confidence to invest more. This finding underlines the importance of supporting export activities and promoting policies that facilitate sales growth.

The proportion of tangible assets does not show statistical significance in explaining investment decisions, consistent with mixed evidence in the literature. Similarly, the risk profile variable does not prove significant, contrary to some studies that emphasise the importance of considering risk profiles in understanding investment behaviours. This may indicate that the other explanatory variables considered in this research play a more fundamental role.

The ability to generate internal financial resources, measured by cash flow, consistently influences the investment rate. This aligns with the literature, which highlights the importance of stable cash flows in fostering robust and consistent investment patterns. Companies with strong cash flows are better positioned to finance new projects without relying excessively on external funding. This financial autonomy improves their ability to respond quickly to market opportunities. Therefore, maintaining healthy cash flows is essential to sustain long-term investment activities and overall business growth.

The analysis reveals a positive relationship between the company size (measured by sales) and the investment rate. However, the nuanced nature of the results, especially in the difference GMM model, highlights the complexity of the size-related effects on investment, imposing careful consideration of the chosen econometric model.

Newer companies were found to tend to invest more than their longer-established counterparts, supporting the insights of Evans (1987) and Geroski (1995). The U-shaped pattern observed in the relationship between the investment rate and the age of the companies suggests that both younger and older companies exhibit higher investment rates, reflecting various operational needs and strategic considerations (Audretsch & Mahmood, 1995; Baptista & Swann, 1998; Cefis & Marsili, 2006). Younger companies often require significant initial investments to establish themselves. In contrast, mature companies might invest to maintain their competitiveness or innovate. This dual trend highlights the varied investment motivations in different stages of the company's life cycle.

Regarding individual company characteristics, such as location of the head office and industry, results consistently reinforce the general findings. However, it was found that there were some nuanced differences, which underlines the importance of considering specific contexts and variables to understand the intricacies of investment dynamics within distinct categories.

Given the relevance of this topic, it is recommended to integrate information on state fiscal support at the company level into future analyses, considering its potential influence on company investment behaviour. Recognising the substantial portion of companies exhibiting zero net investment deserves further study, suggesting the need for models that account for attrition. In addition, fiscal policies such as tax incentives or subsidies could play a critical role. Exploring these elements will provide a clearer picture of how fiscal support impacts investment decisions.

In addition, the role of human capital in the shaping of investment decisions has emerged as a crucial area for future exploration. Understanding how the qualifications and capabilities of the workforce of a company influence investment strategies can offer valuable insights for academic research and the creation of targeted public policies. Therefore, future studies should examine whether education and training initiatives influence corporate investment. This knowledge is important in developing policies that support economic growth.

As final observations, this chapter not only unveiled the trends and determinants of companies' investments in Portugal, but also pointed to future research directions. The complex relationship between economic, regional, and individual company factors provides a rich landscape for ongoing exploration, contributing to a deeper understanding of the dynamics driving corporate investment decisions and their broader implications for economic development. The following chapter delves into the relationship between investment and labour productivity in Portuguese companies, exploring how investment decisions impact the productivity outcomes of the companies.

# CHAPTER IV – INVESTMENT AND LABOUR PRODUCTIVITY IN PORTUGUESE COMPANIES

The intricate relationship between business investment and labour productivity has been a central subject in economic research for decades (Solow, 1956; Romer, 1990; Aghion & Howitt, 1992). This chapter explores the dynamic interplay between these two variables, for the specific case of Portuguese companies, since it remains under explored. The importance of understanding this relationship lies not only in its potential to inform corporate strategies but also in its broader implications for macroeconomic policy, especially within the context of the European Union (EU) , where investment in both capital and human resources is pivotal for long-term economic stability and growth.

Historically, economic theories have underscored the role of capital accumulation as a fundamental driver of productivity. The neoclassical growth model proposed by Solow (1956) introduced the idea that physical capital accumulation is essential to expand the production per worker, with technological progress acting as a complementary factor. Romer (1990) building on this foundation, introduced the concept of endogenous growth, emphasizing the importance of innovation, knowledge, and human capital in driving sustainable economic growth. Aghion and Howitt (1992) further refined this by proposing that the constant process of creative destruction, facilitated by investments in new technologies, drives productivity growth.

Despite these foundational theories, the empirical literature on the relationship between business investment and labour productivity is varied, with differing conclusions drawn about the strength and direction of this relationship across different industries, countries, and economic contexts. Numerous studies at the industry and firm levels have confirmed that investment in both physical and human capital significantly enhances productivity (Foster et al., 2001; Bloom et al., 2012). However, these studies often focus on more developed economies or large-scale industries, with less emphasis on small and medium-sized enterprises (SMEs) or specific countries like Portugal, which presents a gap in the current literature.

Portugal, as part of the European Union, faces distinct economic challenges, including a lower investment rate compared to its northern counterparts and a workforce that, while increasingly educated, still lags behind in terms of productivity levels. This research aims to address this gap by examining the relationship between business investment, human capital, and labour productivity specifically in Portuguese companies over the period 2010 to 2019. The chapter seeks to contribute to the understanding of how investments in physical and human capital, particularly in the context of SMEs, can improve productivity outcomes.

Furthermore, this research adds to the growing body of work that emphasizes the complementarity between physical and human capital in driving productivity. Although traditional economic models often treat physical and human capital as separate inputs, recent empirical work has highlighted how these forms of capital interact synergistically. The work of Aghion and Howitt (1992) and Black and Lynch (2001) demonstrated that investments in physical capital, such as machinery and technology, are more effective when accompanied by a skilled workforce capable of using these technologies to their full potential. This interaction between physical and human capital is especially pertinent in the digital age, where technological advancements rapidly alter the landscape of productivity, requiring workers to continuously adapt and innovate.

The findings of this research are particularly timely, given the ongoing economic transformations spurred by technological disruption and the increasing emphasis on innovation and skill development in global economies. Understanding how investment in both physical and human capital contributes to productivity growth in Portugal is critical for policymakers and business leaders. It will enable them to make informed decisions regarding resource allocation and workforce development, which are crucial for enhancing the country's competitiveness within the European Union and globally.

This research explores the unique dynamics of investment and productivity in Portugal, contributing to the theoretical discourse on capital accumulation while offering practical insights for policymakers seeking to foster economic growth through strategic investments. Specifically, it underscores the importance of aligning investments in physical capital with human capital development to ensure that Portugal's workforce is equipped with the skills necessary to meet the demands of a rapidly changing economic environment. By examining how physical and human capital interact to drive productivity, the study not only extends theoretical understanding but also provides empirical evidence that can inform policy decisions for promoting sustainable economic growth. In doing so, it bridges the gap between macroeconomic theory and microeconomic practice, with implications for both academic research and real-world business strategy.

The chapter is organised as follows. Section 4.1 presents the sources and data used, providing a detailed composition of the sample. Section 4.2 introduces the econometric model, and Section 4.3 discusses the estimation results, including the interaction between physical and human capital, and the model's expansion to include lags. Finally, Section 4.4 summarises the key conclusions and remarks.

## 4.1 Data

The data used in this chapter were derived from the Integrated Business Accounts System (IBAS), as was the case in the previous chapter. This database is the result of the integration of statistical information on businesses. Additionally, the information concerning individual enterprises was excluded because they exhibit distinct behavioural patterns and offer a more limited range of economic and financial indicators. The IBAS database includes a total of 676,382 distinct companies operating in industries A to S, excluding financial and insurance activities (industry K), and public administration and defence, compulsory social security (industry O), of CAE Rev. 3. This dataset spans over a decade, covering the years 2010 to 2019, resulting in a total of 3,869,726 observations throughout the period.

Since the IBAS database does not include information on employees, it was necessary to join this database with another one, called the Single Report, which provided details on workers, including their qualification levels, age, seniority, among other attributes. This link was facilitated using an anonymous key provided by Statistics Portugal. The integration of these two databases enabled a more comprehensive analysis of the factors influencing labour productivity, encompassing both business investment and workforce characteristics. The Single Report is a census-type statistical operation, resulting from an administrative procedure coordinated by the Office of Strategy and Planning of the Ministry of Labour, Solidarity and Social Security. This report is mandatory for all entities with employees, except central, regional, and local administrations and public institutes, excluded from this study.

The dependent variable is the logarithm of labour productivity, represented by the ratio of GVA to persons employed. The following explanatory variables are considered in the models. Primarily, the measure of how much a company invests per employee is examined, shown as the logarithm of total investment per person employed. This reveals the capital investment relative to the workforce, providing insights into resource allocation and the impact of capital spending on overall productivity.

Another important variable is the percentage of employees with higher (tertiary) education, which evaluates the educational composition of the workforce, providing insights into the potential for innovation and skill improvement. The interaction between investment and worker education explores how these factors work together, examining their combined influence on performance outcomes.

The logarithm of personnel costs per person employed offers insights into how personnel expenses relate to productivity and reveals the cost-effectiveness of workforce management. Regarding the characteristics of the workforce, the logarithm of the average age of the employees examines the correlation between the age composition of the workforce and labour productivity. The employee experience, measured by the logarithm of the average seniority of the employees, plays a pivotal role in influencing productivity.

Considering the company's longevity, the logarithm of the age of the company investigates how a company's operational efficiency and organisational maturity correlate with its productivity. A geographical breakdown is also considered, accounting for the location of the company's head office within the seven regions of Portugal, according to the nomenclature of territorial units for statistics, level 2 (NUTS 2): North, Centre, Lisbon Metropolitan Area, Alentejo, Algarve, Autonomous Region of the Azores and Autonomous Region of Madeira.

The company size classification is also taken into account as explanatory variables, as in the previous chapter, that encompass micro, small, medium-sized, and large enterprises based on the number of persons employed. This classification provides a proxy for the company size, facilitating more granular analyses of productivity within distinct strata of business behaviour.

Table 6 provides a comprehensive overview of the descriptive statistics related to the main variables considered in the database. The main advantages of using these data are not only the quantity of information available but also its quality, as it comes from an official source. With more than 3 million observations covering 676,382 distinct companies, the dataset provides a solid foundation for the analysis. The correlation matrix reveals low levels of correlation, indicating that there are no issues of strong correlations between the explanatory variables, which is beneficial for the robustness of the econometric models used.

Table 6. Main descriptive statistics

| Variable | Mean | Median | Standard deviation | No. of observations |
|---|---|---|---|---|
| Logarithm of labour productivity | 9.437541 | 9.547995 | 1.18995 | 3,006,357 |
| Logarithm of total investment per person employed | 7.652028 | 7.634080 | 2.00537 | 1,646,658 |
| Percentage of employees with higher education (undergraduate degree or higher) | 0.179474 | 0.000000 | 0.30577 | 2,195,714 |
| Logarithm of personnel costs per person employed | 9.127375 | 9.234887 | 0.94928 | 3,088,605 |
| Logarithm of the average age of employees | 3.730437 | 3.737670 | 0.19538 | 2,196,653 |
| Logarithm of the average seniority of employees | 1.564055 | 1.734601 | 1.01955 | 2,010,176 |
| Logarithm of the age of the company | 2.144675 | 2.302585 | 1.05793 | 3,598,696 |

Source: Authors' calculations based on data from IBAS, Statistics Portugal.

## 4.2 The econometric model

To assess the significance of investment in the economic performance of companies, several regressions were performed. In these regressions, the dependent variable was the natural logarithm of GVA per person employed for each company, which serves as an indicator of economic performance. The investment from the previous period was included as a regressor. This approach allows for the examination of how past investments influence current economic outcomes, providing insights into the temporal effects of capital allocation on company performance.

The regression is based on a Cobb-Douglas production function within the Solow growth model, considering labour-augmenting technological progress:

$$Y_t = A_t \cdot K_t^{\alpha} \cdot (AL_t)^{1-\alpha} \tag{4.1}$$

where $Y_t$ is the output at time $t$, $A_t$ represents the Total Factor Productivity (TFP), $K_t$ is the quantity of physical capital at time $t$, $L_t$ is the quantity of labour input at time $t$, $A$ and $\alpha$ are parameters, with $0 < \alpha < 1$.

The division of Equation (4.1) by the quantity of labour ($L_t$) yields the expression (4.2) for the output per worker ($y_t$), which is a common transformation in the Solow model:

$$y_t = \frac{Y_t}{L_t} = A_t \cdot \left(\frac{K_t}{L_t}\right)^{\alpha} \cdot \left(\frac{AL_t}{L_t}\right)^{1-\alpha} \tag{4.2}$$

Simplifying further:

$$y_t = A_t \cdot k_t^{\alpha} \tag{4.3}$$

where $y_t$ is the output per worker at time $t$, $A_t$ is the TFP, $k_t = K_t/L_t$ is the capital per worker at time $t$, $\alpha$ is the output elasticity of capital (a parameter between 0 and 1).

Taking the natural logarithm of the expression for output per worker ($y_t$) and applying the logarithm properties, the following expression is obtained:

$$\ln(y_t) = \ln(A_t) + \alpha \ln(k_t) \tag{4.4}$$

The log-linearised form is often used in empirical analysis as it transforms the multiplicative relationships into additive ones. In this form $\ln(y_t)$ denotes the natural logarithm of output per worker at time $t$, $\ln(A_t)$ is the natural logarithm of TFP, and $\ln(k_t)$ is the natural logarithm of capital per worker at time $t$. The parameter $\alpha$ is the capital output elasticity, constrained between 0 and 1.

Equation (4.4) implies a positive relationship between output per worker and capital per worker, consistent with the decreasing marginal returns to capital, where the marginal product of capital decreases as capital increases.

However, recognising that the output per worker is also influenced by the delayed effects of investment, the empirical specification extends Equation (4.4) to include lagged effects and interaction terms. The estimated regression model is as follows:

$$\begin{gathered} \ln\left(produtiv_{i,t}\right) = \beta_0 + \beta_1 \ln\left(investpc_{i,t}\right) + \beta_2 heduc_{i,t} + \\ \beta_3 \ln\left(investpc_{i,t}\right) heduc_{i,t} + \textstyle\sum_z X_{i,t,z} + \eta_i + \upsilon_{i,t} \\ i = 1, \dots, N \\ t = 1, \dots, T \\ z = 4, \dots, Z \end{gathered} \tag{4.5}$$

where $\ln\left(produtiv_{i,t}\right)$ corresponds to the logarithm of productivity of the company $i$ in period $t$, measured by the division of the ratio between GVA and the number of persons employed, $\ln\left(investpc_{i,t}\right)$ represents the logarithm of investment per person employed of the company $i$ in period $t$, $heduc_{i,t}$ is the percentage of persons employed with tertiary education (undergraduate degree or higher) in the company $i$ in period $t$, and the

$\ln(investpc_{i,t})\, heduc_{i,t}$ corresponds to the interaction between the logarithm of investment per person employed and the proportion of workers with higher education. The $X_{i,t,z}$ represent the vectors of the explanatory variables of company $i$ in period $t$. The term $\eta_i$ captures unobserved heterogeneity constant over time, and $\upsilon_{i,t}$ represents the error term.

The characteristics of the companies considered in this study are divided into two groups. In the first group, the characteristics are associated with dummy variables, which take a value of one or zero, depending on whether the characteristic in question is present in company $i$. This group includes the following characteristics: company size, according to the statistical classification of micro, small, medium, or large (based on the level of employment); industry; geographical location of the company's headquarters; and year.

In the second group of variables, the following four characteristics are considered for each company: the logarithm of personnel costs per employee, the logarithm of the average age of the employees, the logarithm of the average seniority of the employees, and the logarithm of the age of the company.

The estimation methods used in the analysis are the Ordinary Least Squares (OLS) estimator, the Fixed Effects (FE) estimator, the difference Generalized Method of Moments (GMM) and the system GMM estimators.

## 4.3 Estimation results

Table 7 presents the estimation results of Equation (4.5). The logarithm of investment per person employed has demonstrated statistical significance at the 1% level in explaining the logarithm of apparent labour productivity between the various estimators. The coefficient exhibits consistency, ranging from 0.0900 in the pooled OLS to 0.0273 in the system GMM. This positive relationship indicates that, on average, a 1% increase in investment per person employed results in a roughly 0.027% increase in apparent labour productivity, according to the coefficient derived from the system GMM estimator.

This result is in line with the work of Solow (1956), who considers that the accumulation of physical capital is a driving force for economic expansion. It is also consistent with Romer (1990), who identifies investment as a pathway to sustained economic growth, impacting labour productivity by improving knowledge and ideas.

Furthermore, it supports the findings of Aghion and Howitt (1992), which indicate that strategic investments contribute to increased labour productivity over time.

Taking into account the proportion of employees with higher education, the result also shows a positive relationship with apparent labour productivity, being significant at 1% in any of the models. For each additional point in the education ratio, for example, an increase of 1 pp, a relative increase of 10.7% is expected in apparent labour productivity, considering the coefficient of the system GMM estimator. This finding aligns with those of Mankiw et al. (1992), Psacharopoulos and Patrinos (2004), and Hanushek and Woessmann (2012), which emphasise the positive nexus between education levels and productivity results.

The results are also consistent for the other variables in the four estimated models, namely the logarithm of personnel costs, the logarithm of the average age of workers, the logarithm of the average seniority of workers, and the logarithm of the age of the company.

Among these last four variables, only the average age of the workers shows a negative relationship with productivity, with the coefficient varying between -0.0405 in difference GMM and -0.0878 in FE. This indicates that for a 1% increase in the average age of the workforce, there is, on average, a 0.04% decrease in apparent labour productivity according to the difference GMM estimator and a 0.09% reduction if the FE estimator is considered.

Regarding the logarithm of personnel costs per person employed, the average seniority of personnel, and the age of the company, the results indicate positive impacts when these variables increase. For example, regarding the system GMM results, a 1% increase in these variables is expected to result in an average increase in apparent labour productivity of 0.96%, 0.0007% and 0.03%, respectively.

### 4.3.1 Interaction between physical and human capital

The analysis of the potential complementarity between physical and human capital within Portuguese companies is a focal point of this research, inspired by the literature that indicates such synergies in diverse national contexts. This research is based on the understanding that the relationship between physical and human capital is pivotal in enhancing productivity in business operations. Building upon insights from the literature, this section delves into how these two forms of capital interact and contribute to the apparent labour productivity of companies, highlighting their relationship.

Based on the literature review, it becomes clear that the interaction between advanced technology and a skilled workforce enhances efficiency and innovation (Arrow, 1962; Black & Lynch, 2001). This highlights the reliance of physical capital, which is composed of machinery, technology, and infrastructure, on skilled human capital for optimal use. The alignment of human capital with physical capital requirements is fundamental in driving productivity gains through skill use and adaptability (Becker, 2009).

The results presented in Table 7 support the existence of a relationship between physical and human capital (variable $lninvest_{i,t} * heduc_{i,t}$) to explain the logarithm of apparent labour productivity within enterprises. Across all estimates, the consistent positive signs of the coefficients indicate a significant positive relationship between this interaction term and apparent labour productivity.

For example, the pooled OLS estimation reveals a coefficient of 0.0101, which means an increase in labour productivity with each unit increase in the interaction term, keeping the other variables constant and significant at the 1% level. In the FE estimation, although the coefficient decreases slightly to 0.0009, it remains statistically significant, which confirms the robustness of the relationship. Furthermore, both the difference GMM and the system GMM estimations yield significant coefficients of 0.0086 and 0.0126, respectively, reassuming a positive association between the complementary effects of physical and human capital on apparent labour productivity.

These empirical results collectively highlight the synergistic contribution of investments in both physical and human capital to improve productivity within enterprises. They emphasise the importance of considering the interconnected dynamics of investment and education in fostering economic efficiency and growth, as presented in the literature review (Arrow, 1962; Black & Lynch, 2001; Becker, 2009). Understanding the relationship between physical and human capital enables companies to adapt to technological advancements, maximise productivity and ensure long-term success in today’s dynamic business environment. This relationship is a critical driver of productivity and innovation in enterprises, as evidenced by the results. By embracing this

Table 7. Model estimates for logarithm of productivity

| Dependent variable: *lnproductiv$_{i,t}$* | Pooled OLS (1) | | | FE (2) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| *lninvestpc$_{i,t}$* | 0.0900 | 0.0007 | *** | 0.0245 | 0.0005 | *** |
| *heduc$_{i,t}$* | 0.0184 | 0.0069 | *** | 0.0118 | 0.0047 | *** |
| *lninvest$_{i,t}$*heduc$_{i,t}$* | 0.0101 | 0.0029 | *** | 0.0009 | 0.0004 | *** |
| *lnemplcostpc$_{i,t}$* | 0.9486 | 0.0034 | *** | 0.7578 | 0.0051 | *** |
| *lnemplage$_{i,t}$* | -0.0436 | 0.0069 | *** | -0.0878 | 0.0100 | *** |
| *lnemplseniority$_{i,t}$* | 0.0057 | 0.0015 | *** | 0.0352 | 0.0021 | *** |
| *lnage$_{i,t}$* | 0.0322 | 0.0016 | *** | 0.0197 | 0.0035 | *** |
| *e1t9$_{i,t}$* | 0.0038 | 0.0010 | *** | 0.0171 | 0.0016 | *** |
| *e10t49$_{i,t}$* | 0.0040 | 0.0010 | *** | 0.0108 | 0.0015 | *** |
| *e50t249$_{i,t}$* | 0.0084 | 0.0010 | *** | 0.0545 | 0.0140 | *** |
| *ege250$_{i,t}$* | - | - | | - | - | |
| *agrc$_{i,t}$* | - | - | | - | - | |
| *manf$_{i,t}$* | 0.1734 | 0.0063 | *** | 0.0402 | 0.0034 | *** |
| *enrg$_{i,t}$* | 0.2939 | 0.0333 | *** | 0.0944 | 0.0583 | |
| *cons$_{i,t}$* | 0.1426 | 0.0065 | *** | 0.0212 | 0.0036 | *** |
| *trad$_{i,t}$* | 0.1448 | 0.0062 | *** | 0.0070 | 0.0033 | ** |
| *tran$_{i,t}$* | 0.1934 | 0.0072 | *** | 0.0285 | 0.0041 | *** |
| *infr$_{i,t}$* | 0.3300 | 0.0068 | *** | 0.0041 | 0.0043 | |
| *accm$_{i,t}$* | 0.2061 | 0.0090 | *** | 0.0009 | 0.0436 | |
| *othr$_{i,t}$* | 0.1473 | 0.0066 | *** | 0.0042 | 0.0035 | |
| *north$_{i,t}$* | 0.0518 | 0.0082 | *** | 0.2207 | 0.0882 | *** |
| *centre$_{i,t}$* | 0.0485 | 0.0082 | *** | 0.2271 | 0.0897 | *** |
| *lisbon$_{i,t}$* | 0.0526 | 0.0083 | *** | 0.1601 | 0.0866 | * |
| *alentejo$_{i,t}$* | 0.0102 | 0.0090 | | 0.1892 | 0.0942 | ** |
| *algarve$_{i,t}$* | 0.0283 | 0.0091 | *** | 0.2285 | 0.1101 | ** |
| *azores$_{i,t}$* | - | - | | - | - | |
| *madeira$_{i,t}$* | 0.0392 | 0.0117 | *** | 0.1832 | 0.1659 | |
| *2015$_{i}$* | 0.0839 | 0.0027 | *** | 0.0723 | 0.0024 | *** |
| *2016$_{i}$* | 0.0915 | 0.0027 | *** | 0.0849 | 0.0025 | *** |
| *2017$_{i}$* | 0.1018 | 0.0026 | *** | 0.1004 | 0.0027 | *** |
| *2018$_{i}$* | 0.0865 | 0.0027 | *** | 0.0892 | 0.0029 | *** |
| *2019$_{i}$* | 0.0828 | 0.0027 | *** | 0.0902 | 0.0031 | *** |
| *constant* | 0.3508 | 0.0402 | *** | 2.2430 | 0.1084 | *** |
| R-squared | 0.4759 | | | 0.437 | | |
| Observations | 1,029,865 | | | 1,029,865 | | |

Table 7. (continuation)

| Dependent variable: $lnproductiv_{i,t}$ | Difference GMM (3) | | | System GMM (4) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $lninvestpc_{i,t}$ | 0.0126 | 0.0009 | *** | 0.0273 | 0.0009 | *** |
| $heduc_{i,t}$ | 0.0867 | 0.0394 | ** | 0.1072 | 0.0257 | *** |
| $lninvest_{i,t}*heduc_{i,t}$ | 0.0086 | 0.0026 | *** | 0.0126 | 0.0028 | *** |
| $lnemplcostpc_{i,t}$ | 0.7730 | 0.0061 | *** | 0.9646 | 0.0039 | *** |
| $lnemplage_{i,t}$ | -0.0405 | 0.0129 | *** | -0.0731 | 0.0072 | *** |
| $lnemplseniority_{i,t}$ | 0.0692 | 0.0027 | *** | 0.0007 | 0.0004 | * |
| $lnage_{i,t}$ | 0.0013 | 0.0005 | *** | 0.0293 | 0.0017 | *** |
| $e1t9_{i,t}$ | 0.0156 | 0.0015 | *** | 0.0008 | 0.0004 | * |
| $e10t49_{i,t}$ | 0.0938 | 0.0141 | *** | 0.0207 | 0.0105 | ** |
| $e50t249_{i,t}$ | 0.0478 | 0.0122 | *** | 0.0120 | 0.0021 | *** |
| $ege250_{i,t}$ | - | - | | - | - | |
| $agrc_{i,t}$ | - | - | | - | - | |
| $manf_{i,t}$ | 0.1012 | 0.0468 | ** | 0.2517 | 0.0067 | *** |
| $enrg_{i,t}$ | 0.1166 | 0.0768 | | 0.3037 | 0.0353 | *** |
| $cons_{i,t}$ | 0.0780 | 0.0483 | | 0.2319 | 0.0069 | *** |
| $trad_{i,t}$ | 0.0970 | 0.0450 | ** | 0.2270 | 0.0066 | *** |
| $tran_{i,t}$ | 0.1103 | 0.0595 | * | 0.2281 | 0.0076 | *** |
| $infr_{i,t}$ | 0.1153 | 0.0629 | * | 0.4452 | 0.0072 | *** |
| $accm_{i,t}$ | 0.1146 | 0.0606 | * | 0.2575 | 0.0110 | *** |
| $othr_{i,t}$ | 0.0969 | 0.0463 | ** | 0.2068 | 0.0079 | *** |
| $north_{i,t}$ | 0.2433 | 0.0656 | *** | 0.0523 | 0.0087 | *** |
| $centre_{i,t}$ | 0.2249 | 0.0670 | *** | 0.0400 | 0.0088 | *** |
| $lisbon_{i,t}$ | 0.2060 | 0.0598 | *** | 0.0434 | 0.0090 | *** |
| $alentejo_{i,t}$ | 0.2523 | 0.0728 | *** | 0.0022 | 0.0096 | |
| $algarve_{i,t}$ | 0.2482 | 0.0991 | *** | 0.0247 | 0.0097 | *** |
| $azores_{i,t}$ | - | - | | - | - | |
| $madeira_{i,t}$ | 0.0608 | 0.1993 | | 0.0403 | 0.0124 | *** |
| $2015_i$ | 0.0311 | 0.0033 | *** | 0.1100 | 0.0025 | *** |
| $2016_i$ | 0.0324 | 0.0037 | *** | 0.1267 | 0.0025 | *** |
| $2017_i$ | 0.0369 | 0.0042 | *** | 0.1420 | 0.0025 | *** |
| $2018_i$ | 0.0160 | 0.0046 | *** | 0.1315 | 0.0025 | *** |
| $2019_i$ | 0.0031 | 0.0051 | | 0.1293 | 0.0026 | *** |
| *constant* | - | - | | 0.8383 | 0.0430 | *** |
| R-squared | - | | | - | | |
| Observations | 1,029,865 | | | 1,029,865 | | |

# Table 7. (continuation)

Source: Authors' calculations based on data from IBAS, Statistics Portugal.

Notes: Significance levels: ***, 1%; **, 5%; *, 10%. The dependent variable in the four models is the logarithm of the productivity, measured by the GVA per person employed. The number of observations considered in each model is the one presented in the table. The difference GMM estimator of Arellano and Bond was obtained at 2 steps, with strictly exogenous variables. The system GMM estimator was obtained at 1 step with strictly exogenous variables. Through the analysis of the Sargan test results, it can be verified that the instruments used in the GMM estimators are valid and can be used in the estimation. The instruments used in the system GMM also do not reject the null hypothesis for a significance level of 2.5%.

dual investment strategy, companies can enhance their competitive edge and achieve higher labour productivity. As the business landscape continues to evolve, the importance of prioritising and supporting the harmonious development of both forms of capital will only intensify, making it imperative for companies and policymakers alike.

### 4.3.2 Expansion of the models by accounting for lags

Expanding on the model presented in Equation (4.5) to incorporate four lags of three variables, namely the logarithm of investment per person employed, the percentage of workers with higher education, and the interaction variable between investment and the qualification of workers, provides an understanding of their impact on apparent labour productivity. The estimation results are presented in Table 8.

Regarding the logarithm of investment per person employed, the findings indicate persistent effects over the years, presenting a statistically significant positive relationship with apparent labour productivity at 1%, except for the fourth lag in the FE model, where the result is not statistically significant. In particular, the system GMM estimator identifies the same lag as significant only at 10%. Furthermore, there is a visible temporal evolution in the impact of this variable, with a decreasing coefficient over time, from 0.0366 in the period $t$ to 0.0015 in the period $t-4$. This implies that on average, the impact on apparent labour productivity of investment per person employed diminishes over time.

Focusing on the percentage of workers with higher education, the results underscore their significance in explaining apparent labour productivity across most lags. In the FE, difference GMM and system GMM models, this variable is significant at the 1% level up to the third lag, whereas in the pooled OLS model it is significant up to the fourth lag. It is important to note that most models reveal a diminishing impact over time, with the coefficient in period t of the system GMM estimator at 0.0629, decreasing to 0.0384 in period $t-3$ (0.4667 and 0.0969, respectively, considering the difference GMM).

The complementarity between investment in physical capital and workers' qualifications, in explaining apparent productivity, reveals consistent findings across models. However, the effects are not statistically significant throughout the period, with the system GMM achieving significance at the 1% level only up to the period $t-2$, and

Table 8. Model estimates for logarithm of productivity, considering lags in some explanatory variables

| Dependent variable: $lnproductiv_{i,t}$ | Pooled OLS (1) | | | FE (2) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $lninvestpc_{i,t}$ | 0.0533 | 0.0011 | *** | 0.0197 | 0.0010 | *** |
| $lninvestpc_{i,t-1}$ | 0.0351 | 0.0009 | *** | 0.0097 | 0.0009 | *** |
| $lninvestpc_{i,t-2}$ | 0.0264 | 0.0009 | *** | 0.0064 | 0.0009 | *** |
| $lninvestpc_{i,t-3}$ | 0.0222 | 0.0009 | *** | 0.0043 | 0.0008 | *** |
| $lninvestpc_{i,t-4}$ | 0.0200 | 0.0010 | *** | -0.0001 | 0.0008 | |
| $heduc_{i,t}$ | 0.0151 | 0.0036 | *** | 0.0261 | 0.0102 | *** |
| $heduc_{i,t-1}$ | 0.0624 | 0.0179 | *** | 0.0306 | 0.0097 | *** |
| $heduc_{i,t-2}$ | 0.0106 | 0.0047 | *** | 0.0725 | 0.0273 | *** |
| $heduc_{i,t-3}$ | 0.0379 | 0.0158 | *** | 0.0430 | 0.0259 | * |
| $heduc_{i,t-4}$ | 0.0121 | 0.0052 | *** | 0.0263 | 0.0244 | |
| $lninvest_{i,t}*heduc_{i,t}$ | 0.0099 | 0.0045 | ** | 0.0011 | 0.0003 | *** |
| $lninvest_{i,t-1}*heduc_{i,t-1}$ | 0.0116 | 0.0042 | *** | 0.0015 | 0.0006 | *** |
| $lninvest_{i,t-2}*heduc_{i,t-2}$ | 0.0061 | 0.0019 | *** | 0.0078 | 0.0031 | *** |
| $lninvest_{i,t-3}*heduc_{i,t-3}$ | 0.0038 | 0.0037 | | 0.0052 | 0.0028 | * |
| $lninvest_{i,t-4}*heduc_{i,t-4}$ | 0.0143 | 0.0037 | *** | 0.0041 | 0.0026 | |
| $lnemplcostpc_{i,t}$ | 0.9116 | 0.0072 | *** | 0.7611 | 0.0140 | *** |
| $lnemplage_{i,t}$ | -0.0339 | 0.0153 | ** | -0.0980 | 0.0255 | *** |
| $lnemplseniority_{i,t}$ | 0.0542 | 0.0037 | *** | 0.0633 | 0.0056 | *** |
| $lnage_{i,t}$ | -0.0057 | 0.0039 | | -0.0404 | 0.0158 | *** |
| $e1t9_{i,t}$ | 0.0861 | 0.0122 | *** | 0.1791 | 0.0201 | *** |
| $e10t49_{i,t}$ | 0.0415 | 0.0117 | *** | 0.1118 | 0.0188 | *** |
| $e50t249_{i,t}$ | 0.0138 | 0.0121 | | 0.0582 | 0.0160 | *** |
| $ege250_{i,t}$ | - | - | | - | - | |
| $agrc_{i,t}$ | - | - | | - | - | |
| $manf_{i,t}$ | 0.0680 | 0.0101 | *** | 0.0611 | 0.0268 | *** |
| $enrg_{i,t}$ | 0.2731 | 0.0429 | *** | 0.0280 | 0.0432 | |
| $cons_{i,t}$ | 0.0298 | 0.0113 | *** | 0.0893 | 0.0299 | *** |
| $trad_{i,t}$ | 0.0001 | 0.0101 | | 0.0790 | 0.0272 | *** |
| $tran_{i,t}$ | 0.1187 | 0.0129 | *** | 0.0163 | 0.0687 | |
| $infr_{i,t}$ | 0.0434 | 0.0114 | *** | 0.1191 | 0.0404 | *** |
| $accm_{i,t}$ | 0.1022 | 0.0159 | *** | 0.0288 | 0.0392 | |
| $othr_{i,t}$ | 0.0634 | 0.0112 | *** | 0.0393 | 0.0294 | |

Table 8. (continuation)

| Dependent variable: *lnproductiv*$_{i,t}$ | Pooled OLS (1) | | | FE (2) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $north_{i,t}$ | 0.0086 | 0.0138 | | 0.2312 | 0.0486 | *** |
| $centre_{i,t}$ | 0.0229 | 0.0139 | * | 0.2138 | 0.0495 | *** |
| $lisbon_{i,t}$ | 0.0193 | 0.0144 | | 0.1930 | 0.0091 | *** |
| $alentejo_{i,t}$ | 0.0079 | 0.0155 | | 0.1625 | 0.0885 | * |
| $algarve_{i,t}$ | 0.0308 | 0.0155 | ** | 0.2905 | 0.0706 | *** |
| $azores_{i,t}$ | - | - | | - | - | |
| $madeira_{i,t}$ | 0.0420 | 0.0223 | * | 0.4525 | 0.3216 | |
| $2015_i$ | 0.0279 | 0.0030 | *** | 0.0138 | 0.0027 | *** |
| $2016_i$ | 0.0324 | 0.0033 | *** | 0.0189 | 0.0034 | *** |
| $2017_i$ | 0.0332 | 0.0033 | *** | 0.0288 | 0.0041 | *** |
| $2018_i$ | 0.0078 | 0.0035 | *** | 0.0150 | 0.0050 | *** |
| $2019_i$ | -0.0034 | 0.0035 | | 0.0126 | 0.0060 | ** |
| *constant* | 0.0743 | 0.0811 | | 2.3392 | 0.1727 | *** |
| R-squared | 0.5595 | | | 0.493 | | |
| Observations | 224,886 | | | 224,886 | | |

Table 8. (continuation)

| Dependent variable: $lnproductiv_{i,t}$ | Difference GMM (3) | | | System GMM (4) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $lninvestpc_{i,t}$ | 0.0366 | 0.0030 | *** | 0.0375 | 0.0018 | *** |
| $lninvestpc_{i,t-1}$ | 0.0213 | 0.0020 | *** | 0.0220 | 0.0015 | *** |
| $lninvestpc_{i,t-2}$ | 0.0140 | 0.0015 | *** | 0.0141 | 0.0014 | *** |
| $lninvestpc_{i,t-3}$ | 0.0084 | 0.0012 | *** | 0.0099 | 0.0013 | *** |
| $lninvestpc_{i,t-4}$ | 0.0015 | 0.0009 | * | 0.0050 | 0.0011 | *** |
| $heduc_{i,t}$ | 0.4667 | 0.1504 | *** | 0.0629 | 0.0103 | *** |
| $heduc_{i,t-1}$ | 0.2715 | 0.0629 | *** | 0.0174 | 0.0099 | * |
| $heduc_{i,t-2}$ | 0.2076 | 0.0459 | *** | 0.0755 | 0.0091 | *** |
| $heduc_{i,t-3}$ | 0.0969 | 0.0366 | *** | 0.0384 | 0.0208 | * |
| $heduc_{i,t-4}$ | 0.0054 | 0.0272 | | 0.0264 | 0.0364 | |
| $lninvest_{i,t}*heduc_{i,t}$ | 0.0441 | 0.0099 | *** | 0.0018 | 0.0008 | *** |
| $lninvest_{i,t-1}*heduc_{i,t-1}$ | 0.0278 | 0.0066 | *** | 0.0038 | 0.0016 | *** |
| $lninvest_{i,t-2}*heduc_{i,t-2}$ | 0.0221 | 0.0051 | *** | 0.0075 | 0.0029 | *** |
| $lninvest_{i,t-3}*heduc_{i,t-3}$ | 0.0110 | 0.0040 | *** | 0.0057 | 0.0052 | |
| $lninvest_{i,t-4}*heduc_{i,t-4}$ | 0.0009 | 0.0029 | | 0.0010 | 0.0041 | |
| $lnemplcostpc_{i,t}$ | 0.7771 | 0.0131 | *** | 0.9260 | 0.0096 | *** |
| $lnemplage_{i,t}$ | -0.0445 | 0.0148 | *** | -0.0467 | 0.0165 | *** |
| $lnemplseniority_{i,t}$ | 0.0855 | 0.0063 | *** | 0.0334 | 0.0037 | *** |
| $lnage_{i,t}$ | -0.0328 | 0.0193 | * | -0.0004 | 0.0039 | |
| $e1t9_{i,t}$ | 0.1532 | 0.0195 | *** | 0.0780 | 0.0119 | *** |
| $e10t49_{i,t}$ | 0.0930 | 0.0183 | *** | 0.0241 | 0.0114 | ** |
| $e50t249_{i,t}$ | 0.0462 | 0.0158 | *** | 0.0050 | 0.0115 | |
| $ege250_{i,t}$ | - | - | | - | - | |
| $agrc_{i,t}$ | - | - | | - | - | |
| $manf_{i,t}$ | 0.0557 | 0.0310 | * | 0.1459 | 0.0115 | *** |
| $enrg_{i,t}$ | 0.0391 | 0.0569 | | 0.2758 | 0.0460 | *** |
| $cons_{i,t}$ | 0.1001 | 0.0333 | *** | 0.1405 | 0.0132 | *** |
| $trad_{i,t}$ | 0.1109 | 0.0631 | * | 0.0985 | 0.0120 | *** |
| $tran_{i,t}$ | 0.0519 | 0.0321 | | 0.1606 | 0.0141 | *** |
| $infr_{i,t}$ | 0.1177 | 0.0389 | *** | 0.1658 | 0.0139 | *** |
| $accm_{i,t}$ | 0.0860 | 0.0515 | * | 0.2279 | 0.0260 | *** |
| $othr_{i,t}$ | 0.0687 | 0.0326 | ** | 0.1775 | 0.0183 | *** |

Table 8. (continuation)

| Dependent variable: *lnproductiv*$_{i,t}$ | Difference GMM (3) | | | System GMM (4) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| *north*$_{i,t}$ | 0.3621 | 0.0592 | *** | 0.0170 | 0.0145 | |
| *centre*$_{i,t}$ | 0.3388 | 0.0611 | *** | 0.0194 | 0.0146 | |
| *lisbon*$_{i,t}$ | 0.3560 | 0.0403 | *** | 0.0108 | 0.0155 | |
| *alentejo*$_{i,t}$ | 0.2462 | 0.0693 | *** | 0.0188 | 0.0162 | |
| *algarve*$_{i,t}$ | 0.4561 | 0.0972 | *** | 0.0291 | 0.0161 | * |
| *azores*$_{i,t}$ | - | - | | - | - | |
| *madeira*$_{i,t}$ | 0.5023 | 0.2934 | * | 0.0498 | 0.0232 | ** |
| *2015*$_{i}$ | 0.0101 | 0.0029 | *** | 0.0226 | 0.0026 | *** |
| *2016*$_{i}$ | 0.0101 | 0.0043 | *** | 0.0305 | 0.0031 | *** |
| *2017*$_{i}$ | 0.0102 | 0.0057 | * | 0.0367 | 0.0033 | *** |
| *2018*$_{i}$ | -0.0093 | 0.0072 | | 0.0183 | 0.0034 | *** |
| *2019*$_{i}$ | -0.0188 | 0.0086 | ** | 0.0102 | 0.0036 | *** |
| *constant* | - | - | | 0.6143 | 0.1003 | *** |
| R-squared | - | | | - | | |
| Observations | 157,633 | | | 224,886 | | |

Source: Authors' calculations based on data from IBAS, Statistics Portugal.

Notes: Significance levels: ***, 1%; **, 5%; *, 10%. The dependent variable in the four models is the logarithm of the productivity, measured by the GVA per person employed. The number of observations considered in each model is the one presented in the table. The difference GMM estimator of Arellano and Bond was obtained at 2 steps, with strictly exogenous variables. The system GMM estimator was obtained at 1 step with strictly exogenous variables. Through the analysis of the Sargan test results, it can be verified that the instruments used in the GMM estimators are valid and can be used in the estimation. The instruments used in the system GMM also do not reject the null hypothesis for a significance level of 2.5%.

the difference GMM model achieving significance up to the period $t - 3$. The impact of this variable does not follow a clear trend over time, exhibiting higher coefficients in the period $t - 2$ in the FE and system GMM models (0.0078 and 0.0075, respectively) and higher coefficients in the period $t$ in the difference GMM (0.0441) and $t - 1$ in the pooled OLS (0.0116).

These results offer an understanding of the relationship between investment and qualifications over time, illustrating how they impact productivity. This underscores the importance of ongoing research and adaptive strategies in business investment and education policies to maximise productivity gains. It also indicates that policymakers and business leaders should consider these dynamic interactions when developing strategies to enhance economic performance and sustain long-term growth.

Recognising the pivotal role of investment in enhancing company productivity, as highlighted in the previous findings, it is crucial to understand whether the benefits of investment persist for a longer period. This research delves into the temporal dimension of investment impacts, with the objective of determining whether the positive effects on productivity are sustained in the long run. Such insights are important for both corporate decision-makers and policymakers in developing long-term business strategies.

To address this, the system GMM estimator was used to examine the long-term impact, including up to nine lags, according to the expanded Equation (4.5) detailed in Section 4.2. The results shown in Table 9 indicate that, while the influence of investment diminishes over time, it exhibits a lasting and significant effect throughout the analysed period. Specifically, in the initial year, a 1% increase in investment per person employed is, on average, correlated with a 0.21% increase in apparent labour productivity. Even in the final available lag, this impact persists, though with a smaller magnitude, registering around 0.02%.

There is a consensus among researchers that current levels of productivity are influenced by the cumulative effects of past investments. This notion highlights the enduring impact of historical investment decisions on current economic performance, highlighting the importance of a proactive investment approach to promote sustained productivity growth (Mokyr et al., 2015).

Table 9. Model estimates for logarithm of productivity, considering nine lags

| Dependent variable: *lnproductiv*$_{i,t}$ | System GMM | | |
|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| *lninvestpc*$_{i,t}$ | 0.2103 | 0.0764 | *** |
| *lninvestpc*$_{i,t-1}$ | 0.1356 | 0.0492 | *** |
| *lninvestpc*$_{i,t-2}$ | 0.1021 | 0.0367 | *** |
| *lninvestpc*$_{i,t-3}$ | 0.0825 | 0.0292 | *** |
| *lninvestpc*$_{i,t-4}$ | 0.0615 | 0.0220 | *** |
| *lninvestpc*$_{i,t-5}$ | 0.0476 | 0.0173 | *** |
| *lninvestpc*$_{i,t-6}$ | 0.0378 | 0.0140 | *** |
| *lninvestpc*$_{i,t-7}$ | 0.0283 | 0.0105 | *** |
| *lninvestpc*$_{i,t-8}$ | 0.0190 | 0.0063 | *** |
| R-squared | - | | |
| Observations | 19,131 | | |

Source: Authors' calculations based on data from IBAS, Statistics Portugal.

Notes: Significance levels: ***, 1%; **, 5%; *, 10%. The dependent variable is the logarithm of the productivity, measured by the GVA per person employed. The number of observations considered in the model is the one presented in the table. The model also included other control variables, namely dummies for size-classes, industries, geographical location and years. The difference GMM estimator of Arellano and Bond was obtained at 2 steps, with strictly exogenous variables. The system GMM estimator was obtained at 1 step with strictly exogenous variables. Through the analysis of the Sargan test results, it can be verified that the instruments used in the GMM estimators are valid and can be used in the estimation. The instruments used in the system GMM also do not reject the null hypothesis for a significance level of 2.5%.

This finding highlights the persistent nature of the impact of investment on labour productivity, indicating that initial increases continue to have effects over the years. It aligns with the notion that investment serves as a catalyst for technological change within companies, contributing to sustained productivity gains (Romer, 1990; Stiroh, 2000).

Recent economic studies focus on the important role of technological evolution in shaping investment dynamics and subsequent productivity outcomes, indicating that modern investment practices are increasingly integrated with technological advancements, contrasting sharply with older models. This shift towards technologically driven investment is considered more efficient and productive, reflecting the transformative power of innovation in today’s markets (Acemoglu & Restrepo, 2020).

## 4.4 Conclusions and remarks

In this chapter, business investment and productivity have been extensively explored. Empirical results consistently reveal a statistically significant positive relationship between the logarithm of investment per person employed and apparent labour productivity. This implies that increased investment is associated with higher productivity, aligning with foundational economic theories such as the Solow model.

The percentage of employees with tertiary education shows a positive and significant association with apparent labour productivity. This finding aligns with the broader literature that emphasises the role of human capital, particularly education, in driving economic growth and productivity improvements. By fostering a more educated workforce, companies can improve their productivity and contribute to overall economic development.

The analysis reveals that the positive relationship between investment and productivity diminishes over time, indicating that initial boosts in productivity from increased investment have a lasting but diminishing effect. This indicates that while investment remains crucial for growth, its impact decreases as capital ages, highlighting the importance of continuous investment to sustain productivity gains.

As the results indicate, the exploration of the complementarity between physical and human capital highlights their symbiotic relationship. Skilled workers are essential for the optimal use of physical capital, leading to increased efficiency, innovation and overall productivity. This emphasises the need for companies to invest not only in advanced technologies, but also in the education and training of their workforce.

Examining the lasting effects of investment over a nine-year period reveals that the influence of investment persists, although with diminishing magnitudes. The enduring nature of the impact of investment on labour productivity reinforces its role as a catalyst for sustained technological change.

The findings have implications for both policymakers and business leaders. Policymakers may consider creating incentives for investment to improve productivity. Business leaders can leverage these insights to sustain decisions about resource allocation and workforce development. By aligning investment strategies with the goal of improving human capital qualifications, both groups can contribute to sustainable economic growth.

Future research could explore the specific mechanisms through which investment affects productivity, including industry-specific dynamics and the effect of innovation. Furthermore, examining how external factors, such as economic shocks or policy changes, interact with the observed relationships would offer a more complete picture of the dynamics at play.

Another suggestion is to explore the distinction in human capital, particularly considering individuals with a higher education in engineering or mathematics and those without. This would investigate whether companies with a larger proportion of workers with higher education in these fields have a more significant impact on productivity compared to other workers. Additionally, the study would be extended to determine if there is a cross effect with investment that reinforces this behaviour. This approach acknowledges the potential specialised skills and knowledge that engineering or mathematics education provides, which may have distinct effects on productivity compared to other forms of higher education. By specifically focusing on workers with engineering backgrounds, the analysis can uncover any unique contributions they make to productivity within the context of Portuguese companies.

This differentiation in human capital is crucial as it allows for a more granular examination of the workforce composition and its impact on labour productivity. It also aligns with previous research suggesting that certain types of education may have a stronger influence on productivity due to the technical expertise and problem solving skills they offer (Acemoglu & Autor, 2011; Barro & Lee, 2013). By exploring the interaction between investment and the presence of workers with engineering education, the analysis seeks to understand whether investments in technology and infrastructure are used and leveraged more effectively by companies with a higher proportion of engineering talent. This exploration can provide insight into how investments interact with specific composition of human capital to enhance productivity.

In conclusion, this chapter contributes to the ongoing discourse on the relationship between business investment and labour productivity, offering a better understanding of the dynamics within the context of Portuguese companies, considering the period from 2010 to 2019. The findings underscore the importance of investing in driving labour productivity growth while also highlighting the long-lasting effect over time. Finally, exploring of the complementarity between physical and human capital provides valuable insight into the synergistic effects of skilled labour and capital investment on overall labour productivity.

# CHAPTER V – INVESTMENT AND EMPLOYMENT LEVEL IN PORTUGUESE COMPANIES

The relationship between investment and employment is pivotal in shaping a nation's economic trajectory, influencing not only productivity, but also long-term economic growth. Among the factors driving this relationship, innovation stands out as a critical driver of both economic dynamism and the expansion of employment opportunities. The Lisbon Strategy[9] of the European Union, for example, highlights the importance of fostering innovation to improve productivity, stimulate economic growth, and create new jobs (European Commission, 2005). These objectives are more relevant than ever, as economies worldwide face the dual challenge of technological advancement and workforce adaptation.

Scholars have long debated the effects of technological change on employment. Although some argue that innovation leads to the displacement of workers due to automation and the evolving nature of jobs (Acemoglu & Autor, 2011; Autor et al., 2003), others highlight the potential for job creation in emerging industries driven by new technologies (Brynjolfsson & McAfee, 2012). Technological advancements, particularly those related to innovation, can generate new employment opportunities, although they also introduce challenges such as job displacement and skill mismatches. This dual impact underlines the importance of exploring not only the types of jobs created but also the kinds of workers who are most likely to benefit from such changes.

This chapter contributes to this debate by examining the relationship between investment and employment, with a particular focus on product innovation measured by research and development (R&D) expenditures. Although capital investment, such as machinery and infrastructure, is a traditional driver of employment growth, R&D investment, which fosters product and process innovation, provides a more nuanced perspective on job creation.

While process innovation often involves the integration of new fixed capital, R&D efforts are typically aimed at developing new prototypes or patents, introducing entirely new products, or significantly improving existing ones (Dosi, 1988; Nelson & Winter, 1982; Rosenberg, 1976). However, empirical studies on the subject often yield mixed

[9] Action and development plan devised in 2000 for the economy of the European Union between 2000 and 2010.

results, depending on the industry, the type of innovation, and the educational level of the workforce involved. For example, product innovation, related to the development of new goods and services, often requires highly skilled labour, which can lead to a growth of employment in knowledge-intensive industries (Bogliacino et al., 2012; Piva & Vivarelli, 2005). In contrast, process innovation, which typically involves the automation of existing production processes, can lead to job displacement, particularly for lower-skilled workers (Acemoglu & Autor, 2011).

The existing literature reveals significant sectoral and regional differences in the employment effects of innovation. While high-tech industries often exhibit strong positive associations between R&D spending and job creation, low-tech and service industries may see negligible or even negative effects (Buerger et al., 2012; Van Roy et al., 2018). Moreover, the impact of innovation on employment is not uniform across the workforce. Studies show that individuals with higher education qualifications tend to benefit more from innovation-driven growth, given their involvement in more complex, skill-intensive roles (Coad & Rao, 2010). This highlights the need for policies that not only encourage innovation but also support skill development and education to ensure that the broader workforce can adapt to changing technological demands.

In light of these complexities, this chapter aims to provide a comprehensive analysis of the relationship between investment, innovation, and employment in Portuguese companies. This research is particularly timely given the ongoing discussions about the future of work and the role of technological advancement in shaping labour markets. Moreover, it contributes to the literature by offering new insights into the Portuguese context, a country with unique challenges and opportunities within the broader European framework.

This chapter is structured as follows. Section 5.1 delves into the data used for the analysis, providing a detailed composition of the sample of Portuguese companies. Section 5.2 presents the econometric model, while Section 5.3 provides the main estimation results. Section 5.4 summarises the main findings and remarks.

## 5.1 Data

The data used for the analysis in this chapter are derived from the Integrated Business Accounts System (IBAS), as was the case in the previous chapters. This database is the result of the integration of statistical information on businesses. Once more, the information about individual enterprises was excluded because they exhibit distinct behavioural patterns and offer a more limited range of economic and financial indicators. The IBAS database includes a total of 676,382 distinct companies operating in industries A to S, excluding financial and insurance activities (industry K), and public administration and defence, compulsory social security (industry O), of CAE Rev. 3. This dataset spans over a decade, covering the years 2010 to 2019, resulting in a total of 3,869,726 observations throughout the period.

Since the IBAS database does not include information on employees, it was necessary to link this database to another one, called the Single Report, which provided details on workers, including their qualification levels, age, seniority, among other attributes. This link was facilitated using an anonymous key provided by Statistics Portugal. The integration of these databases allowed for more comprehensive analysis of the factors that influence labour productivity, encompassing both business investment and workforce characteristics. The Single Report is a statistical operation of the census type, resulting from an administrative procedure coordinated by the Strategy and Planning Office of the Ministry of Labour, Solidarity and Social Security. It is mandatory for all entities with employees, except for central, regional, and local administrations and public institutes, excluded from this study.

Furthermore, the data from the Scientific and Technological Potential Survey were joined to previous databases to include the variable R&D expenditure by company. This survey collects statistical information on R&D activities in Portugal, targeting all companies potentially conducting R&D activities in Portugal, and refers to the activity carried out during the reference year of the survey. The linking of microdata was once again made possible by the anonymous key provided by Statistics Portugal. The integration of these data sources facilitates the exploration of the relationships between investment and R&D expenditures and workforce characteristics.

The dependent variable is the logarithm of the level of employment based on the number of persons employed ($\ln(empl_{i,t})$). The inclusion of the logarithm of the persons employed in the previous period ($\ln(empl_{i,t-1})$) accounts for the dynamic nature of employment. It captures the inertia or momentum in employment levels, indicating how past employment influences current employment levels. This lagged variable is essential for understanding the persistence and adjustments in employment over time.

Personnel costs per person employed reflect the average expenditure on labour ($perslcostpc_{i,t}$). The logarithmic transformation of this variable helps in the analysis of the elasticity of employment with respect to personnel costs. It provides information on how changes in labour costs influence employment decisions, revealing the cost-effectiveness of workforce management (Gollop & Jorgenson, 1980).

Net investment refers to the amount of capital invested ($invest_{i,t}$). Using the logarithm of this variable, the model assesses how investment influences employment. This variable facilitates comprehension of the relationship between capital expenditure and labour demand, illustrating how investment strategies impact overall productivity and employment levels (Chirinko, 1993).

GVA measures the value of goods and services produced by a company ($gva_{i,t}$). This variable is crucial in assessing the economic performance of a company and its capacity to generate employment through increased production (Hulten, 2001).

R&D expenditures indicate a company's investment in innovation and technological advancement ($r\&d_{i,t}$). The logarithm of R&D expenditures provides insight into the impact of innovation on employment, as higher R&D spending could lead to more skilled employment opportunities and improved productivity (Hall et al., 2010).

The econometric analysis also considers the industry in which the company operates. Different industries have different labour demands and productivity dynamics. Including dummy variables for industries allows the model to control for industry-specific effects and better isolate the impact of other variables on the employment level. Nine groups were considered: agriculture and fishing, manufacturing, energy and water, construction and real estate, distributive trade, accommodation and food services, transportation and storage, information and communication, and other services.

The location of a company's head office is also considered within the seven NUTS 2 regions of Portugal (North, Centre, Lisbon Metropolitan Area, Alentejo, Algarve, Autonomous Region of the Azores, and Autonomous Region of Madeira) is also considered. This regional categorisation captures the geographical disparities in economic conditions, infrastructure, and labour markets in Portugal. By including geographical breakdowns, the model can account for regional variations that might influence employment.

Table 10 provides an overview of the descriptive statistics relating to the main variables of the database considered in this chapter. The correlation matrix reveals low levels of correlation, which not cause problems at the level of strong correlations between the explanatory variables.

Table 10. Main descriptive statistics

| Variable | Mean | Median | Standard deviation | No. of observations |
|---|---|---|---|---|
| Logarithm of persons employed | 0.910902 | 0.693147 | 1.071757 | 3,869,726 |
| Logarithm of personnel costs per person employed | 9.127375 | 9.234887 | 0.949280 | 3,088,605 |
| Logarithm of net investment | 9.023371 | 9.049219 | 2.095679 | 1,646,658 |
| Logarithm of R&D expenditures | 11.34365 | 11.437060 | 1.792801 | 26,992 |
| Logarithm of gross value added | 10.53887 | 10.548990 | 1.765923 | 2,994,784 |

Source: Authors' calculations based on data from IBAS, Single Report and NSTPS and Directorate-General for Education and Science Statistics.

## 5.2 The econometric model

Employment levels tend to be stable over time, with changes likely to persist rather than fluctuate significantly. This pattern is confirmed by a simple regression in the first lag of employment, which yields a value close to 1 (Nickell, 1981; Blanchard & Summers, 1986; Gali, 1999; Stock & Watson, 1999). Therefore, a conventional dynamic employment equation was employed to account for this persistence.

The equation accounts for the autoregressive nature of employment and its dependence on output (value added), wages, and investment. Estimating an employment equation often benefits from a panel dynamic specification, as demonstrated by Arellano and Bond (1991). Consequently, the derived equation embodies a conventional dynamic labour demand model, in line with the frameworks described by Van Reenen (1997) and Bogliacino and Vivarelli (2012).

$$\ln(empl_{i,t}) = \alpha \cdot \ln(empl_{i,t-1}) + \beta_0 + \beta_1 \cdot \ln(perslcostpc_{i,t}) + \beta_2 \cdot \ln(invest_{i,t}) + \beta_3 \cdot \ln(gva_{i,t}) + \textstyle\sum_z \beta_z X_{i,t,z} + \eta_i + \upsilon_{i,t} \tag{5.1}$$

$$i = 1, \dots, N$$

$$t = 1, \dots, T$$

$$z = 4, \dots, Z$$

where $i$ and $t$ indicate, respectively, the company and the reference period, $empl$ is the level of employment, $perslcostpc$ are the personnel costs per person employed, $invest$ is gross fixed capital formation or investment, $gva$ is the gross value added. The $X$ represent the vectors of other explanatory variables. The term $\eta$ captures the unobserved heterogeneity constant over time, and $\upsilon$ represents the error term.

In order to analyse the relationship between investment and employment, it is necessary to consider Equation (5.1) as a foundation for the analysis. To enrich the model under consideration, it is necessary to incorporate a proxy for technological change. To capture the effects of innovation on employment dynamics, a variable representing company-level R&D expenditures is introduced.

Taking this approach, the present study expands the scope of the analysis beyond traditional investment measures, encompassing the role of innovation in shaping employment outcomes. This expanded equation enables exploration of how investment in R&D, which is frequently associated with the development of new products or processes, influences the levels of employment within companies.

$$\ln(empl_{i,t}) = \alpha \cdot \ln(empl_{i,t-1}) + \beta_0 + \beta_1 \cdot \ln(perslcostpc_{i,t}) + \beta_2 \cdot \ln(invest_{i,t}) + \beta_3 \cdot \ln(r\&d_{i,t}) + \beta_4 \cdot \ln(gva_{i,t}) + \textstyle\sum_z \beta_z X_{i,t,z} + \eta_i + \upsilon_{i,t} \tag{5.2}$$

$$i = 1, \dots, N$$

$$t = 1, \dots, T$$

$$z = 5, \dots, Z$$

To refine the analysis of the impact of investment and R&D expenditure on employment, it is important to differentiate the dependent variable in Equation (5.2) by the qualification of the persons employed. This approach ensures a more detailed understanding of how investment and R&D expenditure influence employment in different segments of the workforce. Specifically, a distinction will be made between those employed with higher education qualifications (undergraduate degree or higher) and those without such qualifications.

The rationale behind this differentiation lies in the premise that determinants of employment can exert different degrees of influence depending on the education level of the workforce. Individuals with higher education qualifications can show different responses to factors such as wages, investment, and innovation compared to those without higher education. For instance, R&D expenditures might have a more pronounced impact on employment levels among highly qualified employees, given their likely participation in knowledge-intensive and innovative activities (Coad & Rao, 2010). Conversely, traditional investment in capital formation may have a stronger effect on employment for those without higher education qualifications, reflecting the nature of the roles typically associated with such investments (Van Reenen, 1997).

This differentiation facilitates a deeper understanding of how key economic factors influence employment dynamics in different educational segments, providing valuable information for more tailored and effective labour market policies (Van Reenen, 1997; Bogliacino & Vivarelli, 2012). Having this concept in mind, the Equation (5.2) can be modified to separately account for the employment levels of individuals with and without higher or tertiary education. The revised equation is thus represented as follows:

$$\begin{gathered} \ln\left(empl_{i,t,q}\right) = \alpha_q \cdot \ln\left(empl_{i,t-1,q}\right) + \beta_{0,q} + \beta_{1,q} \cdot \ln\left(perslcostpc_{i,t,q}\right) \\ + \beta_{2,q} \cdot \ln(invest_{i,t,q}) + \beta_{3,q} \cdot \ln(r\&d_{i,t,q}) + \beta_{4,q} \cdot \ln(gva_{i,t,q}) + \\ + \textstyle\sum_z \beta_{z,q} X_{i,t,z,q} + \eta_{i,q} + \upsilon_{i,t,q} \qquad (5.3) \\ i = 1, \dots, N \\ t = 1, \dots, T \\ z = 4, \dots, Z^* \\ q \in \{high, low\} \end{gathered}$$

where $empl_{i,t,q}$ represents the level of employment of individuals in the company $i$, at time $t$ with the qualification status $q$, where $q$ can be either "high" (for those with higher or tertiary education) or "low" (for those without). The coefficients $\alpha_q$ and $\beta_{0\ldots z,q}$ are specific to the qualification status and capture the impact of the distinction of the explanatory variables on the respective groups. The terms $\eta_{i,q}$ and $\upsilon_{i,t,q}$ represent the unobserved heterogeneity and the error term, respectively, for each qualification group.

## 5.3 Estimation results

Table 11 presents the estimation results of the four econometric models, where the dependent variable is the natural logarithm of employment ($\ln(empl_{i,t})$). The dependent variable lagged ( $\ln(empl_{i,t-1})$ ) exhibits strong persistence in all models, with coefficients ranging from 0.3923 in the FE model to 0.7965 in the pooled OLS model.

This finding aligns with Blanchard and Katz (1992), who highlighted the persistent nature of employment due to labour market rigidities and adjustment costs.

Personnel costs per person employed ($perslcostpc_{i,t}$) consistently show a negative and significant impact on employment. The system GMM model reveals the most substantial effect (-0.3044). This result corroborates the theories of labour economics that indicate that higher labour costs can prevent the creation of jobs (Hamermesh, 1996). The negative relationship indicates that increased personnel costs can lead companies to reduce their workforce to control expenses.

Investment emerged as a significant positive determinant of employment in all the econometric models used in the research. The investment coefficients ($\ln(invest_{i,t})$) range from 0.0084 in the system GMM model to 0.0167 in the pooled OLS model, consistent with the evidence that increased capital formation stimulates job creation. According to neoclassical growth theory, investment in physical capital enhances productivity, leading to a greater demand for labour (Solow, 1956; Romer, 1990; Aghion & Howitt, 1998; Acemoglu & Zilibotti, 2001).

Investment consistently shows a positive and significant effect on employment in all models. The pooled OLS model (coefficient 0.0167) indicates that a 1% increase in investment is associated with a 1.67% increase in employment, highlighting the substantial impact of capital formation on job creation. By controlling for unobserved heterogeneity, the FE model (coefficient 0.0128) indicates that within company variations in investment are positively linked to employment, underscoring the role of company-level and regional investment activities.

Addressing potential endogeneity, the difference GMM results (coefficient of 0.0084) confirm the positive effect of investment, indicating that past investment decisions positively influence current employment levels. The system GMM model (coefficient of 0.0155), which combines differenced and level equations, indicates that investment improves employment, even after accounting for endogeneity and dynamic panel biases.

GVA ($\ln(gva_{i,t})$) emerges as a significant positive determinant of employment, with the system GMM model showing the highest coefficient (0.2026). This finding indicates that the higher gross value added by companies contributes to increased employment, reflecting the importance of economic output in creating jobs. The detailed results underscore this relationship across various econometric models. Specifically, the pooled

OLS model yields a coefficient of 0.1456, the FE model shows a coefficient of 0.1881, and the difference GMM model indicates a coefficient of 0.1309, all of which are statistically significant at the 1% level.

The results also indicate industry-specific effects on employment, as well as regional and temporal effects, highlighting the various factors that influence employment dynamics. Industry-specific analysis revealed significant variations. For example, the manufacturing industry ($manf_{i,t}$) shows a consistently positive impact on employment across all models, with coefficients ranging from 0.0365 in the system GMM model to 0.1041 in the FE model, indicating robust job creation in this industry. In contrast, the energy and water industry ($enrg_{i,t}$) demonstrates mixed results, with a significant negative coefficient in the pooled OLS and system GMM models (-0.0548 and -0.0466, respectively), suggesting potential job losses, while the FE and difference GMM models show non-significant positive coefficients.

Furthermore, the construction and real estate industry ($cons_{i,t}$) exhibits varied effects, with a positive coefficient in the pooled OLS and system GMM models (0.0309 and 0.0412, respectively) but a negative coefficient in the FE and difference GMM models (-0.0254 and -0.0159, respectively), indicating industry-specific dynamics. The distributive trade industry ( $trad_{i,t}$ ) shows a strong positive relationship with employment, particularly in the system GMM model (0.0334), reflecting the importance of trade activities in the creation of employment.

Regional analysis provides additional insight into employment dynamics. The Centre region ($centre_{i,t}$) stands out with consistently significant positive coefficients across different models, such as 0.0217 in the system GMM model and 0.0151 in the pooled OLS model, highlighting the region's strong job creation capacity. The Lisbon Metropolitan Area ($lisbon_{i,t}$) similarly exhibits positive coefficients, strengthening its role as a major hub for employment. The Algarve ( $algarve_{i,t}$ ) shows a positive coefficient in the FE model (0.1379) but non-significant results in other models, suggesting variability in regional employment effects. Furthermore, the Autonomous Region of Madeira ($madeira_{i,t}$) registers in the difference GMM model (0.2379) a significant positive impact on employment, underscoring regional disparities in employment dynamics.

Table 11. Model estimates for logarithm of persons employed

| Dependent variable: $lnempl_{i,t}$ | Pooled OLS (1) | | | FE (2) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $lnempl_{i,t-1}$ | 0.7965 | 0.0011 | *** | 0.3923 | 0.0020 | *** |
| $lnperslcostpc_{i,t}$ | -0.1049 | 0.0012 | *** | -0.1766 | 0.0026 | *** |
| $lninvest_{i,t}$ | 0.0167 | 0.0002 | *** | 0.0128 | 0.0002 | *** |
| $lngva_{i,t}$ | 0.1456 | 0.0010 | *** | 0.1881 | 0.0014 | *** |
| $agrc_{i,t}$ | 0.0025 | 0.0022 | | 0.0265 | 0.0198 | |
| $manf_{i,t}$ | 0.0609 | 0.0013 | *** | 0.1041 | 0.0137 | *** |
| $enrg_{i,t}$ | -0.0548 | 0.0086 | *** | 0.0349 | 0.0332 | |
| $cons_{i,t}$ | 0.0309 | 0.0014 | *** | -0.0254 | 0.0146 | * |
| $trad_{i,t}$ | 0.0182 | 0.0010 | *** | 0.0034 | 0.0116 | |
| $tran_{i,t}$ | 0.0094 | 0.0017 | *** | 0.0417 | 0.0194 | ** |
| $infr_{i,t}$ | 0.1079 | 0.0016 | *** | 0.0681 | 0.0204 | *** |
| $accm_{i,t}$ | 0.0377 | 0.0027 | *** | 0.0670 | 0.0242 | *** |
| $othr_{i,t}$ | - | - | | - | - | |
| $north_{i,t}$ | 0.0046 | 0.0030 | | 0.0781 | 0.0870 | |
| $centre_{i,t}$ | 0.0151 | 0.0030 | *** | 0.0843 | 0.0865 | |
| $lisbon_{i,t}$ | 0.0159 | 0.0031 | *** | 0.0942 | 0.0851 | |
| $alentejo_{i,t}$ | 0.0156 | 0.0033 | *** | 0.0695 | 0.0887 | |
| $algarve_{i,t}$ | 0.0009 | 0.0034 | | 0.1379 | 0.0953 | |
| $azores_{i,t}$ | - | - | | - | - | |
| $madeira_{i,t}$ | 0.0056 | 0.0042 | | 0.0388 | 0.1201 | |
| $2011_i$ | 0.0006 | 0.0013 | | 0.0255 | 0.0012 | *** |
| $2012_i$ | -0.0096 | 0.0014 | *** | 0.0057 | 0.0011 | *** |
| $2013_i$ | - | - | | - | - | |
| $2014_i$ | 0.0225 | 0.0014 | *** | 0.0133 | 0.0011 | *** |
| $2015_i$ | 0.0261 | 0.0014 | *** | 0.0252 | 0.0012 | *** |
| $2016_i$ | 0.0197 | 0.0014 | *** | 0.0328 | 0.0012 | *** |
| $2017_i$ | 0,0132 | 0,0013 | *** | 0,0411 | 0,0012 | *** |
| $2018_i$ | 0,0084 | 0,0013 | *** | 0,0544 | 0,0013 | *** |
| $2019_i$ | 0,003 | 0,0013 | ** | 0,0633 | 0,0014 | *** |
| *constant* | -0.4726 | 0.0097 | *** | 0.4452 | 0.0871 | *** |
| R-squared | 0.9244 | | | 0.906 | | |
| Observations | 1,117,769 | | | 1,117,769 | | |

Table 11. (continuation)

| Dependent variable: $lnempl_{i,t}$ | Difference GMM (3) | | | System GMM (4) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $lnempl_{i,t-1}$ | 0.4948 | 0.0047 | *** | 0.7084 | 0.0046 | *** |
| $lnperslcostpc_{i,t}$ | -0.3044 | 0.0045 | *** | -0.1555 | 0.0018 | *** |
| $lninvest_{i,t}$ | 0.0084 | 0.0003 | *** | 0.0155 | 0.0002 | *** |
| $lngva_{i,t}$ | 0.1309 | 0.0016 | *** | 0.2026 | 0.0029 | *** |
| $agrc_{i,t}$ | 0.0559 | 0.0268 | ** | 0.0121 | 0.0027 | *** |
| $manf_{i,t}$ | 0.0365 | 0.0190 | * | 0.1028 | 0.0026 | *** |
| $enrg_{i,t}$ | 0.0225 | 0.0436 | | -0.0466 | 0.0109 | *** |
| $cons_{i,t}$ | -0.0159 | 0.0207 | | 0.0412 | 0.0018 | *** |
| $trad_{i,t}$ | 0.0152 | 0.0165 | | 0.0334 | 0.0014 | *** |
| $tran_{i,t}$ | 0.0546 | 0.0249 | ** | 0.0186 | 0.0021 | *** |
| $infr_{i,t}$ | 0.0348 | 0.0294 | | 0.1412 | 0.0028 | *** |
| $accm_{i,t}$ | 0.0443 | 0.0345 | | 0.0487 | 0.0031 | *** |
| $othr_{i,t}$ | - | - | | - | - | |
| $north_{i,t}$ | 0.0903 | 0.0919 | | 0.0006 | 0.0036 | |
| $centre_{i,t}$ | 0.0811 | 0.0911 | | 0.0217 | 0.0036 | *** |
| $lisbon_{i,t}$ | 0.0660 | 0.0853 | | 0.0234 | 0.0037 | *** |
| $alentejo_{i,t}$ | 0.0702 | 0.0908 | | 0.0237 | 0.0039 | *** |
| $algarve_{i,t}$ | 0.0689 | 0.1071 | | 0.0065 | 0.0040 | |
| $azores_{i,t}$ | - | - | | - | - | |
| $madeira_{i,t}$ | 0.2379 | 0.1183 | ** | 0.0043 | 0.0049 | |
| $2011_i$ | 0.0353 | 0.0013 | *** | 0.0084 | 0.0014 | *** |
| $2012_i$ | 0.0034 | 0.0011 | *** | -0.0044 | 0.0014 | *** |
| $2013_i$ | - | - | | - | - | |
| $2014_i$ | 0.0176 | 0.0010 | *** | 0.0166 | 0.0014 | *** |
| $2015_i$ | 0.0309 | 0.0012 | *** | 0.0176 | 0.0014 | *** |
| $2016_i$ | 0.0385 | 0.0014 | *** | 0.0088 | 0.0014 | *** |
| $2017_i$ | 0,0499 | 0,0016 | *** | 0,001 | 0,0015 | |
| $2018_i$ | 0,0633 | 0,0018 | *** | -0,004 | 0,0015 | *** |
| $2019_i$ | 0,0737 | 0,0021 | *** | -0,0149 | 0,0014 | *** |
| *constant* | - | - | | -0.5001 | 0.0220 | *** |
| R-squared | - | | | - | | |
| Observations | 653,079 | | | 1,117,769 | | |

Source: Authors' calculations based on data from IBAS and NSTPS, Statistics Portugal and Directorate-General for Education and Science Statistics.

Notes: Significance levels: ***, 1%; **, 5%; *, 10%. The dependent variable in the four models is the logarithm of the persons employed. The number of observations considered in each model is the one presented in the table. The difference GMM estimator of Arellano and Bond was obtained at 2 steps, with strictly exogenous variables. The system GMM estimator was obtained at 1 step with strictly exogenous variables. Through the analysis of the Sargan test results, it can be verified that the instruments used in the GMM estimators are valid and can be used in the estimation. The instruments used in the system GMM also do not reject the null hypothesis for a significance level of 2.5%.

### 5.3.1 The R&D expenditures in the promotion of employment level

The role of R&D expenditures in promoting the employment level has received significant attention in economic research. The relationship between R&D expenditures and employment is particularly relevant in the context of knowledge-driven economies, where innovation is a key driver of economic performance.

Table 12 presents the estimation results for Equation (5.3), which incorporates the R&D expenditure into the model. The results indicate a positive impact of the logarithm of R&D expenditures ($\ln(r\&d_{i,t})$) on the logarithm of employment. All four estimation methods produced statistically significant and positive coefficients, indicating that higher R&D expenditures are associated with higher levels of employment.

The pooled OLS (coefficient 0.0211) show that a 1% increase in R&D expenditures leads to approximately a 2.11% increase in employment. The FE model shows a slightly higher coefficient (0.0277), reinforcing the positive impact of R&D expenditures. Taking into account potential endogeneity issues, the estimation of the difference GMM presents a coefficient for $\ln(r\&d_{i,t})$ of 0.0135, indicating a more pronounced effect of R&D expenditure on employment compared to the previous models. In the system GMM model, the coefficient is 0.0391, which is lower than in the other models but still significant.

The positive relationship between R&D expenditures and employment underscores the critical role of innovation in economic development. R&D activities frequently promote the creation of new products, services and processes, which can stimulate demand and generate new job opportunities. In addition, the introduction of advanced technologies can improve productivity, leading to growth in various industries. These findings align with the existing literature that highlights the positive effects of R&D expenditures on employment (Coad & Rao, 2010; Bogliacino & Vivarelli, 2012).

The robustness of the results across different econometric methods confirms the positive impact of R&D expenditures on employment levels. Future research could further explore the long-term implications for economic growth and labour market dynamics. This would provide deeper insight into how targeted investments in innovation can drive sustainable development and enhance employment opportunities in various industries.

Table 12. Model estimates for logarithm of persons employed, considering the intramural R&D expenditure as explanatory variable

| Dependent variable: $lnempl_{i,t}$ | Pooled OLS (1) | | | FE (2) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $lnempl_{i,t-1}$ | 0.7781 | 0.0134 | *** | 0.4253 | 0.0243 | *** |
| $lnperslcostpc_{i,t}$ | -0.1791 | 0.0160 | *** | -0.2941 | 0.0308 | *** |
| $lninvest_{i,t}$ | 0.0204 | 0.0017 | *** | 0.0158 | 0.0018 | *** |
| $lnr\&d_{i,t}$ | 0.0211 | 0.0023 | *** | 0.0277 | 0.0028 | *** |
| $lngva_{i,t}$ | 0.1503 | 0.0118 | *** | 0.1796 | 0.0119 | *** |
| $agrc_{i,t}$ | -0.0754 | 0.0232 | *** | 0.2055 | 0.1043 | ** |
| $manf_{i,t}$ | 0.0300 | 0.0084 | *** | 0.1336 | 0.0716 | * |
| $enrg_{i,t}$ | 0.1300 | 0.0256 | *** | 0.1486 | 0.0697 | ** |
| $cons_{i,t}$ | 0.0208 | 0.0146 | | 0.1486 | 0.0863 | * |
| $trad_{i,t}$ | -0.0406 | 0.0103 | *** | 0.0864 | 0.0657 | |
| $tran_{i,t}$ | 0.0050 | 0.0264 | | 0.1677 | 0.0958 | * |
| $infr_{i,t}$ | 0.0632 | 0.0347 | * | - | - | |
| $accm_{i,t}$ | 0.0272 | 0.0094 | *** | 0.0347 | 0.0816 | |
| $othr_{i,t}$ | - | - | | - | - | |
| $north_{i,t}$ | 0.0016 | 0.0250 | | 0.1258 | 0.0500 | *** |
| $centre_{i,t}$ | 0.0054 | 0.0251 | | 0.1122 | 0.0107 | *** |
| $lisbon_{i,t}$ | 0.0062 | 0.0255 | | 0.0546 | 0.0491 | |
| $alentejo_{i,t}$ | 0.0037 | 0.0271 | | 0.0984 | 0.0928 | |
| $algarve_{i,t}$ | 0.0032 | 0.0376 | | 0.0310 | 0.2032 | |
| $azores_{i,t}$ | - | - | | - | - | |
| $madeira_{i,t}$ | 0.0582 | 0.0414 | | - | - | |
| $2011_i$ | 0.0102 | 0.0084 | | 0.0241 | 0.0066 | *** |
| $2012_i$ | 0.0049 | 0.0080 | | 0.0055 | 0.0056 | |
| $2013_i$ | - | - | | - | - | |
| $2014_i$ | 0.0259 | 0.0072 | *** | 0.0307 | 0.0054 | *** |
| $2015_i$ | 0.0266 | 0.0077 | *** | 0.0474 | 0.0063 | *** |
| $2016_i$ | 0.0276 | 0.0075 | *** | 0.0581 | 0.0065 | *** |
| $2017_i$ | 0.0247 | 0.0077 | *** | 0.0755 | 0.0069 | *** |
| $2018_i$ | 0.0389 | 0.0073 | *** | 0.1094 | 0.0077 | *** |
| $2019_i$ | 0.0275 | 0.0074 | *** | 0.1160 | 0.0094 | *** |
| *constant* | 0.0675 | 0.0991 | | 2.0245 | 0.3061 | *** |
| R-squared | 0.9723 | | | 0.960 | | |
| Observations | 20,459 | | | 20,459 | | |

Table 12. (continuation)

| Dependent variable: *$lnempl_{i,t}$* | Difference GMM (3) | | | System GMM (4) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| *$lnempl_{i,t-1}$* | 0.5321 | 0.0307 | *** | 0.4627 | 0.0587 | *** |
| *$lnperslcostpc_{i,t}$* | -0.4107 | 0.0394 | *** | -0.3502 | 0.0333 | *** |
| *$lninvest_{i,t}$* | 0.0117 | 0.0015 | *** | 0.0248 | 0.0023 | *** |
| *$lnr\&d_{i,t}$* | 0.0135 | 0.0026 | *** | 0.0391 | 0.0044 | *** |
| *$lngva_{i,t}$* | 0.0992 | 0.0109 | *** | 0.3814 | 0.0438 | *** |
| *$agrc_{i,t}$* | 0.0656 | 0.0876 | | -0.0793 | 0.0407 | * |
| *$manf_{i,t}$* | 0.0332 | 0.0813 | | 0.0316 | 0.0188 | * |
| *$enrg_{i,t}$* | 0.2075 | 0.0911 | *** | 0.2242 | 0.0522 | *** |
| *$cons_{i,t}$* | -0.0943 | 0.1021 | | 0.1202 | 0.0317 | *** |
| *$trad_{i,t}$* | -0.1058 | 0.0797 | | -0.0488 | 0.0170 | *** |
| *$tran_{i,t}$* | 0.0755 | 0.0449 | * | 0.1081 | 0.0554 | * |
| *$infr_{i,t}$* | - | - | | 0.1900 | 0.0692 | *** |
| *$accm_{i,t}$* | -0.0502 | 0.0690 | | 0.0261 | 0.0139 | * |
| *$othr_{i,t}$* | - | - | | - | - | |
| *$north_{i,t}$* | 0.0302 | 0.0596 | | 0.0003 | 0.0507 | |
| *$centre_{i,t}$* | - | - | | 0.0220 | 0.0511 | |
| *$lisbon_{i,t}$* | 0.0101 | 0.0637 | | 0.0217 | 0.0515 | |
| *$alentejo_{i,t}$* | 0.0233 | 0.0908 | | 0.0154 | 0.0538 | |
| *$algarve_{i,t}$* | 0.1476 | 0.1296 | | 0.0282 | 0.0622 | |
| *$azores_{i,t}$* | - | - | | - | - | |
| *$madeira_{i,t}$* | - | - | | 0.1186 | 0.0857 | |
| *$2011_i$* | 0.0189 | 0.0047 | *** | 0.0163 | 0.0086 | * |
| *$2012_i$* | -0.0015 | 0.0037 | | 0.0138 | 0.0072 | * |
| *$2013_i$* | - | - | | - | - | |
| *$2014_i$* | 0.0335 | 0.0044 | *** | 0.0160 | 0.0068 | *** |
| *$2015_i$* | 0.0441 | 0.0053 | *** | 0.0138 | 0.0078 | * |
| *$2016_i$* | 0.0506 | 0.0062 | *** | 0.0065 | 0.0080 | |
| *$2017_i$* | 0.0742 | 0.0073 | *** | 0.0045 | 0.0087 | |
| *$2018_i$* | 0.0986 | 0.0087 | *** | 0.0225 | 0.0081 | *** |
| *$2019_i$* | 0.1055 | 0.0111 | *** | 0.0080 | 0.0078 | |
| *constant* | - | - | | -0.6121 | 0.2442 | *** |
| R-squared | - | | | - | | |
| Observations | 13,504 | | | 20,459 | | |

Source: Authors' calculations based on data from IBAS and NSTPS, Statistics Portugal and Directorate-General for Education and Science Statistics.

Notes: Significance levels: ***, 1%; **, 5%; *, 10%. The dependent variable in the four models is the logarithm of the persons employed. The number of observations considered in each model is the one presented in the table. The difference GMM estimator of Arellano and Bond was obtained at 2 steps, with strictly exogenous variables. The system GMM estimator was obtained at 1 step with strictly exogenous variables. Through the analysis of the Sargan test results, it can be verified that the instruments used in the GMM estimators are valid and can be used in the estimation. The instruments used in the system GMM also do not reject the null hypothesis for a significance level of 2.5%.

### 5.3.2 Analysis of the impact of investment in the employment by educational qualification

The distinction in employment effects based on employee qualifications is a crucial aspect of understanding the broader impacts of investment and R&D expenditure. Table 13 presents the estimation results considering Equation (5.3) and the dependent variable as the logarithm of persons employed with higher education ($\ln(empl_{i,t,q=high})$). In contrast, Table 14 displays the results considering the same equation, but with the dependent variable as the logarithm of persons employed without higher education ($\ln(empl_{i,t,q=low})$). These tables show the coefficients, robust standard errors, and significance levels for the different estimation methods.

The results indicate that R&D expenditures have a significantly positive impact on employment for both segments of the workforce, whether they have higher education or not, although with different magnitudes and dynamics. For persons employed with higher education ($\ln(empl_{i,t,q=high})$), the results of various models consistently demonstrate a much more positive relationship between R&D expenditures and employment levels.

In the pooled OLS model, the coefficient for the logarithm of R&D expenditure, considering $q = high$ ($\ln(r\&d_{i,t,q=high})$), is 0.0276. This indicates that a 1% increase in the R&D expenditures corresponds to approximately a 0.0276% increase in the number of persons employed with higher education. This effect remains robust in the FE model, with a slightly higher coefficient of 0.0279.

When using the system GMM, the coefficient increased to 0.0501, indicating a stronger impact of R&D expenditures on employment. In the difference GMM model, the coefficient is slightly lower at 0.0130, but remains significant, underscoring the positive influence of R&D expenditures on the employment of persons with higher education. These findings highlight the critical role of R&D expenditures in promoting employment among highly qualified workers.

Regarding persons employed without higher education ($\ln(empl_{i,t,q=low})$), the impact of R&D expenditures on employment levels is considerably smaller than that of those with higher education. In the pooled OLS model, the coefficient for R&D expenditures is 0.0004, indicating a negligible effect. The FE model shows a modest increase with a coefficient of 0.0118, indicating a slight positive impact. The system GMM model yields a coefficient of 0.0015, indicating a minimal effect, while the difference GMM model shows a coefficient of 0.0047, reflecting a small but positive effect. These findings also shows that R&D expenditures have a negligible impact on the employment of persons without higher education, highlighting the need for different types of investment to stimulate employment in this segment of the workforce.

These findings indicate that R&D expenditures predominantly benefit employment among highly educated workers. This may be due to the nature of R&D activities that typically require specialised skills and knowledge, thus favouring higher education employees. The differential impact of R&D expenditures on employment by qualification level is consistent with the existing literature. For example, Aghion et al. (2019) indicated that innovation-driven industries tend to employ a higher proportion of skilled workers, thus disproportionately benefiting those with higher education. Similarly, Coad and Rao (2010) highlighted that companies that invest heavily in innovation and R&D tend to present a higher level of employment among the most qualified individuals, as these roles often involve complex problem solving and advanced technical expertise. Furthermore, Bogliacino and Vivarelli (2012) emphasised that R&D expenditures are closely linked to the creation of high-skilled jobs, typically aimed at individuals with higher education qualifications.

In general, the findings reinforce the notion that R&D expenditures have a more pronounced positive effect on the employment of highly educated workers. This indicates that policies designed to improve R&D should also address educational and training initiatives to maximise employment benefits at all levels of qualification.

Table 13. Model estimates for logarithm of persons employed with higher education

| Dependent variable: $lnempl_{i,t,high}$ | Pooled OLS (1) | | | FE (2) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $lnempl_{i,t-1,high}$ | 0.8594 | 0.0057 | *** | 0.4468 | 0.0138 | *** |
| $lnperslcostpc_{i,t,high}$ | -0.0781 | 0.0101 | *** | -0.2949 | 0.0314 | *** |
| $lninvest_{i,t,high}$ | 0.0150 | 0.0018 | *** | 0.0164 | 0.0022 | *** |
| $lnr\&d_{i,t,high}$ | 0.0276 | 0.0023 | *** | 0.0279 | 0.0033 | *** |
| $lngva_{i,t,high}$ | 0.0710 | 0.0045 | *** | 0.1558 | 0.0109 | *** |
| *constant* | -0.2209 | 0.1003 | ** | 1.8276 | 0.2989 | *** |
| Dummies: | | | | | | |
| Industry | Yes | | | Yes | | |
| Regional | Yes | | | Yes | | |
| Temporal | Yes | | | Yes | | |
| R-squared | 0.9504 | | | 0.891 | | |
| Observations | 18,527 | | | 18,527 | | |

| Dependent variable: $lnempl_{i,t,high}$ | Difference GMM (3) | | | System GMM (4) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $lnempl_{i,t-1,high}$ | 0.5737 | 0.0431 | *** | 0.6762 | 0.0407 | *** |
| $lnperslcostpc_{i,t,high}$ | -0.4137 | 0.0454 | *** | -0.1212 | 0.0140 | *** |
| $lninvest_{i,t,high}$ | 0.0109 | 0.0023 | *** | 0.0163 | 0.0020 | *** |
| $lnr\&d_{i,t,high}$ | 0.0130 | 0.0039 | *** | 0.0501 | 0.0058 | *** |
| $lngva_{i,t,high}$ | 0.0783 | 0.0103 | *** | 0.1788 | 0.0231 | *** |
| *constant* | - | - | | -1.0516 | 0.3084 | *** |
| Dummies: | | | | | | |
| Industry | Yes | | | Yes | | |
| Regional | Yes | | | Yes | | |
| Temporal | Yes | | | Yes | | |
| R-squared | - | | | - | | |
| Observations | 12,378 | | | 18,527 | | |

Source: Authors' calculations based on data from IBAS, Single Report and NSTPS, Statistics Portugal, Ministry of Labour, Solidarity and Social Security and Directorate-General for Education and Science Statistics.

Notes: Significance levels: ***, 1%; **, 5%; *, 10%. The dependent variable in the four models is the logarithm of the persons employed with higher education. The number of observations considered in each model is the one presented in the table. Each model included dummy variables for industries, geographical location at the NUTS 2 level, and time. The difference GMM estimator of Arellano and Bond was obtained at 2 steps, with strictly exogenous variables. The system GMM estimator was obtained at 1 step with strictly exogenous variables. Through the analysis of the Sargan test results, it can be verified that the instruments used in the GMM estimators are valid and can be used in the estimation. The instruments used in the system GMM also do not reject the null hypothesis for a significance level of 2.5%.

Table 14. Model estimates for logarithm of persons employed without higher education

| Dependent variable: $lnempl_{i,t,low}$ | Pooled OLS (1) | | | FE (2) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $lnempl_{i,t-1,low}$ | 0.8634 | 0.0067 | *** | 0.4832 | 0.0180 | *** |
| $lnperslcostpc_{i,t,low}$ | -0.2245 | 0.0173 | *** | -0.4205 | 0.0448 | *** |
| $lninvest_{i,t,low}$ | 0.0188 | 0.0018 | *** | 0.0148 | 0.0022 | *** |
| $lnr\&d_{i,t,low}$ | 0.0004 | 0.0019 | | 0.0118 | 0.0031 | *** |
| $lngva_{i,t,low}$ | 0.1063 | 0.0074 | *** | 0.1829 | 0.0136 | *** |
| *constant* | 0.9270 | 0.1178 | *** | 2.8525 | 0.4103 | *** |
| Dummies: | | | | | | |
| Industry | Yes | | | Yes | | |
| Regional | Yes | | | Yes | | |
| Temporal | Yes | | | Yes | | |
| R-squared | 0.9740 | | | 0.963 | | |
| Observations | 17,248 | | | 17,248 | | |

| Dependent variable: $lnempl_{i,t,low}$ | Difference GMM (3) | | | System GMM (4) | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Rob. Std. Error* | *Sig.* | *Coefficient* | *Rob. Std. Error* | *Sig.* |
| $lnempl_{i,t-1,low}$ | 0.5753 | 0.0549 | *** | 0.6636 | 0.0594 | *** |
| $lnperslcostpc_{i,t,low}$ | -0.4549 | 0.0576 | *** | -0.4537 | 0.0648 | *** |
| $lninvest_{i,t,low}$ | 0.0091 | 0.0023 | *** | 0.0202 | 0.0026 | *** |
| $lnr\&d_{i,t,low}$ | 0.0047 | 0.0037 | | 0.0015 | 0.0030 | |
| $lngva_{i,t,low}$ | 0.0878 | 0.0148 | *** | 0.2741 | 0.0495 | *** |
| *constant* | - | - | | 1.3866 | 0.2090 | *** |
| Dummies: | | | | | | |
| Industry | Yes | | | Yes | | |
| Regional | Yes | | | Yes | | |
| Temporal | Yes | | | Yes | | |
| R-squared | - | | | - | | |
| Observations | 11,582 | | | 17,248 | | |

Source: Authors' calculations based on data from IBAS, Single Report and NSTPS, Statistics Portugal, Ministry of Labour, Solidarity and Social Security and Directorate-General for Education and Science Statistics.

Notes: Significance levels: ***, 1%; **, 5%; *, 10%. The dependent variable in the four models is the logarithm of the persons employed without higher education. The number of observations considered in each model is the one presented in the table. Each model included dummy variables for industries, geographical location at the NUTS 2 level, and time. The difference GMM estimator of Arellano and Bond was obtained at 2 steps, with strictly exogenous variables. The system GMM estimator was obtained at 1 step with strictly exogenous variables. Through the analysis of the Sargan test results, it can be verified that the instruments used in the GMM estimators are valid and can be used in the estimation. The instruments used in the system GMM also do not reject the null hypothesis for a significance level of 2.5%.

## 5.4 Conclusions and remarks

The research presented in this chapter stresses the critical role of investment in shaping employment within Portuguese companies. The persistence of employment, as indicated in the lagged dependent variable, is evident across all models, with coefficients ranging from 0.3923 in the FE model to 0.7965 in the pooled OLS model. This result aligns with Blanchard and Katz (1992), who highlighted the rigidities of the labour market and the adjustment costs. Furthermore, personnel costs per person employed consistently show a negative and significant impact on employment, with the difference GMM model revealing the most substantial effect (-0.3044), corroborating the idea that higher labour costs can discourage employment (Hamermesh, 1996).

Investment emerges as a significant positive determinant of employment. The investment coefficients range from 0.0084 in the difference GMM model to 0.0167 in the pooled OLS model, consistently indicating that increased capital formation stimulates job creation. This positive relationship can be understood through the neoclassical growth theory, which asserts that investment in physical capital improves productivity, leading to economic growth and greater demand for labour (Solow, 1956). Furthermore, Romer (1990) extended this framework by emphasising the role of technological change and innovation, suggesting that investment in R&D and human capital leads to endogenous growth and subsequent increases in employment.

The results also found a clear difference in the influence of R&D expenditures on employment based on educational qualifications. For individuals with higher education qualifications, R&D expenditures significantly improve employment, emphasising the important role of this type of investment in driving job creation for skilled labour, and the need for continuous support and improvement of research or innovative-intensive industries. This is evident from the strong coefficients across the various econometric models considered. The findings are consistent with the broader literature, which suggests that R&D activities inherently demand specialised skills and knowledge, thus benefiting highly educated workers (Aghion et al., 2019; Coad & Rao, 2010; Bogliacino & Vivarelli, 2012).

In contrast, the impact of R&D expenditures on employment for individuals without higher education is minimal. The coefficients for R&D expenditures in this segment remain low in all estimation methods, highlighting a negligible effect. Instead, employment for this group is more responsive to traditional investments in capital formation and GVA. This indicates the need for policies aimed at improving vocational training and skill development to enhance employability and allow these workers to benefit from such investments.

In general, the results emphasise the importance of tailored investment strategies that consider the educational composition of the workforce. While R&D expenditures are crucial in fostering employment among highly educated workers, complementary policies focusing on capital formation and skill enhancement are essential to support employment for those without higher education qualifications. These insights are vital for policymakers aiming to create sustainable employment growth in the Portuguese labour market. By recognising and addressing the diverse needs of the workforce, Portugal can better capitalise on the potential of its human capital in response to evolving economic and technological landscapes.

To further enrich the understanding of the impact of investment and R&D expenditures on employment, future research may consider a longitudinal analysis of industry-specific impacts. Investigating how R&D and other forms of investment influence employment in specific industries over extended periods could provide deeper insight into industrial dynamics and help identify which industries benefit the most from innovation-driven growth. In addition, assessing the impact of emerging technologies is crucial. The study of the effects of technology such as artificial intelligence and automation on employment at various qualification levels can help forecast future labour market trends and develop suitable policy responses. This approach can ensure that the workforce is adequately prepared and supported to adapt to technological advancements.

Future research could also analyse how investment and R&D expenditure influence the emigration of skilled workers, given the recent increase in skilled emigration from Portugal. Understanding this relationship is crucial, as higher investment in R&D might create more opportunities for skilled workers domestically, potentially reducing the emigration rate.

This approach is supported by the idea that better economic conditions and job prospects can retain skilled workers, although economic migration theories suggest that at certain stages of development, better conditions may initially enable migration by easing budget constraints (De Haas, 2010; Winter, 2020). Furthermore, changes in immigration legislation and R&D expenditure have a positive impact on the selection and retention of highly educated workers, indicating that targeted investments could influence skilled migration patterns (Brücker et al., 2012).

By addressing these study areas, researchers and policymakers can achieve a more comprehensive understanding of the impact of investment and R&D expenditure on employment. This deeper insight will ultimately contribute to the development of more effective economic strategies in Portugal.

# CHAPTER VI – CONCLUSION

This research provided a comprehensive analysis of the investment determinants in Portuguese companies from 2010 to 2019, and explored the implications of investment on labour productivity and employment levels. Through the application of econometric analyses and various methodological approaches, this study elucidated the dynamics that influence corporate investment decisions, their effects on productivity, and the subsequent implications for employment, indicating directions for future research.

The evolution of companies' investments during the specified period demonstrates substantial regional, industrial, and size-related variations. Net investment reached its peak in 2019, reflecting significant growth compared to 2010, with the lowest value observed in 2012. Econometric analyses revealed the critical factors that influence investment decisions. A significant association was identified between high levels of indebtedness and lower net investment, indicating a conservative investment approach among companies with substantial debt obligations (Lang et al., 1996; Myers, 1977; Aivazian et al., 2005). Conversely, companies with greater growth potential, as measured by export capacity and sales growth, exhibited higher levels of net investment (Campa & Shaver, 2002; Lang et al., 1996). The ability to generate internal financial resources, such as cash flow, emerged as a significant determinant of investment, highlighting the importance of stable internal funding for investment activities.

A positive relationship was identified between company size (measured by sales) and investment rate. However, the complexity of size-related effects requires careful econometric modelling. The analysis also revealed a U-shaped relationship between company age and investment, with both younger and older companies demonstrating higher investment rates. This indicates that investment motivations vary between different stages of the lifecycle of a company, from initial establishment to the need to maintain competitiveness.

The findings of the study indicate a consistent and statistically significant positive relationship between investment per person employed and labour productivity. The role of human capital, particularly the percentage of employees with tertiary education, was also significant, underscoring the importance of education in enhancing productivity (Acemoglu & Autor, 2011; Barro & Lee, 2013). However, the positive impact of investment on productivity decreased over time, indicating that although initial boosts from increased investment are significant, they wane as capital ages. This finding highlights the need for continuous investment to sustain productivity gains. The complementarity between physical and human capital was evident, and skilled workers improved the efficient use of physical capital, leading to increased productivity.

Regarding the impact of investment on employment, it was found that investment was a significant positive determinant of employment level. This indicates that increased capital formation stimulates job creation, which is consistent with neoclassical growth theory (Solow, 1956; Romer, 1990). With regard to R&D expenditures, they significantly increased employment for individuals with higher education qualifications, emphasising the importance of innovation-driven industries in creating high-skilled jobs. In contrast, the impact of R&D on employment for individuals without higher education was found to be negligible, highlighting the need for policies promoting vocational training and skill development, regardless of their origin, whether from private companies or government initiatives (Aghion et al., 2019; Coad & Rao, 2010).

The findings of this study have significant implications for both policymakers and business leaders. From a policy perspective, the creation of a favourable environment for investment is crucial. This includes the implementation of supportive fiscal policies and incentives for R&D and innovation, the address of labour market rigidities, and the promotion of skill development. Such measures are deemed to encourage employment growth. From a business leadership perspective, understanding the determinants of investment and the factors driving productivity is vital for the formulation of strategic decisions regarding resource allocation and workforce development. The positive relationship between investment and productivity highlights the importance of sustained capital formation and the strategic role of human capital in enhancing competitiveness.

Future research is recommended to explore the specific mechanisms through which investment affects productivity, including industry-specific dynamics and the effect of innovation. Furthermore, analysing how emerging technologies such as artificial intelligence and automation impact employment across different qualification levels could help forecast future labour market patterns. Given the recent increase in skilled emigration from Portugal, it would also be beneficial to investigate the impact of investment and R&D expenditure on skilled worker emigration, which should provide useful information.

In summary, the present study makes important contributions to the fields of corporate finance, labour economics, and economic development. The findings emphasise the critical role of investment in shaping economic outcomes, highlighting the importance of strategic resource allocation and human capital development. As Portugal continues to navigate the evolving economic challenges, the insights of this research offer valuable guidance on fostering labour productivity and economic growth.

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# ANNEXES

# LIST OF ANNEXES

Annex 1. Aggregations of persons employed

| Dummy variable | Dummy variable description |
|---|---|
| e1t9 | 1 to 9 persons employed |
| e10t49 | 10 to 49 persons employed |
| e50t249 | 50 to 249 persons employed |
| ege250 | 250 or more persons employed |

Annex 2. Aggregations of industry

| Dummy variable | Dummy variable description | Sections and divisions of industry |
|---|---|---|
| agrc | Agriculture and fishing | Section A — Agriculture, forestry and fishing, including:<br>- Division 01: Crop and animal production, hunting and related service activities<br>- Division 02: Forestry and logging<br>- Division 03: Fishing and aquaculture |
| manf | Manufacturing | Section B — Mining and quarrying, including:<br>- Division 05: Mining of coal and lignite<br>- Division 06: Extraction of crude petroleum and natural gas<br>- Division 07: Mining of metal ores<br>- Division 08: Other mining and quarrying<br>- Division 09: Mining support service activities<br>Section C — Manufacturing, including:<br>- Division 10: Manufacture of food products<br>- Division 11: Manufacture of beverages<br>- Division 12: Manufacture of tobacco products<br>- Division 13: Manufacture of textiles<br>- Division 14: Manufacture of wearing apparel<br>- Division 15: Manufacture of leather and related products<br>- Division 16: Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials<br>- Division 17: Manufacture of paper and paper products<br>- Division 18: Printing and reproduction of recorded media<br>- Division 19: Manufacture of coke and refined petroleum products<br>- Division 20: Manufacture of chemicals and chemical products<br>- Division 21: Manufacture of basic pharmaceutical products and pharmaceutical preparations<br>- Division 22: Manufacture of rubber and plastic products<br>- Division 23: Manufacture of other non-metallic mineral products<br>- Division 24: Manufacture of basic metals<br>- Division 25: Manufacture of fabricated metal products, except machinery and equipment<br>- Division 26: Manufacture of computer, electronic and optical products<br>- Division 27: Manufacture of electrical equipment |

| Dummy variable | Dummy variable description | Sections and divisions of industry |
|---|---|---|
| | | - Division 28: Manufacture of machinery and equipment n.e.c.<br>- Division 29: Manufacture of motor vehicles, trailers and semi-trailers<br>- Division 30: Manufacture of other transport equipment<br>- Division 31: Manufacture of furniture<br>- Division 32: Other manufacturing<br>- Division 33: Repair and installation of machinery and equipment |
| enrg | Energy and water | Section D — Electricity, gas, steam and air conditioning supply, including:<br>- Division 35: Electricity, gas, steam and air conditioning supply<br>Section E — Water supply; sewerage, waste management and remediation activities, including:<br>- Division 36: Water collection, treatment and supply<br>- Division 37: Sewerage<br>- Division 38: Waste collection, treatment and disposal activities; materials recovery<br>- Division 39: Remediation activities and other waste management services |
| cons | Construction and real estate | Section F — Construction, including:<br>- Division 41: Construction of buildings<br>- Division 42: Civil engineering<br>- Division 43: Specialised construction activities<br>Section L — Real estate activities, including:<br>- Division 68: Real estate activities |
| trad | Distributive trade | Section G — Wholesale and retail trade; repair of motor vehicles and motorcycles, including:<br>- Division 45: Wholesale and retail trade and repair of motor vehicles and motorcycles<br>- Division 46: Wholesale trade, except of motor vehicles and motorcycles<br>- Division 47: Retail trade, except of motor vehicles and motorcycles |
| tran | Transportation and storage | Section H — Transportation and storage, including:<br>- Division 49: Land transport and transport via pipelines<br>- Division 50: Water transport<br>- Division 51: Air transport<br>- Division 52: Warehousing and support activities for transportation<br>- Division 53: Postal and courier activities |

| Dummy variable | Dummy variable description | Sections and divisions of industry |
|---|---|---|
| accm | Accommodation and food services | Section I — Accommodation and food service activities, including:<br>- Division 55: Accommodation<br>- Division 56: Food and beverage service activities |
| infr | Information and communication | Section J — Information and communication, including:<br>- Division 58: Publishing activities<br>- Division 59: Motion picture, video and television programme production, sound recording<br>and music publishing activities<br>- Division 60: Programming and broadcasting activities<br>- Division 61: Telecommunications<br>- Division 62: Computer programming, consultancy and related activities<br>- Division 63: Information service activities |
| othr | Other services | Section M — Professional, scientific and technical activities, including:<br>- Division 69: Legal and accounting activities<br>- Division 70: Activities of head offices; management consultancy activities<br>- Division 71: Architectural and engineering activities; technical testing and analysis<br>- Division 72: Scientific research and development<br>- Division 73: Advertising and market research<br>- Division 74: Other professional, scientific and technical activities<br>- Division 75: Veterinary activities<br><br>Section N — Administrative and support service activities, including:<br>- Division 77: Rental and leasing activities<br>- Division 78: Employment activities<br>- Division 79: Travel agency, tour operator reservation service and related activities<br>- Division 80: Security and investigation activities<br>- Division 81: Services to buildings and landscape activities<br>- Division 82: Office administrative, office support and other business support activities<br><br>Section P — Education, including:<br>- Division 85: Education<br><br>Section Q — Human health and social work activities, including:<br>- Division 86: Human health activities<br>- Division 87: Residential care activities |

| Dummy variable | Dummy variable description | Sections and divisions of industry |
|---|---|---|
| | | - Division 88: Social work activities without accommodation<br><br>Section R — Arts, entertainment and recreation, including:<br>- Division 90: Creative, arts and entertainment activities<br>- Division 91: Libraries, archives, museums and other cultural activities<br>- Division 92: Gambling and betting activities<br>- Division 93: Sports activities and amusement and recreation activities<br><br>Section S — Other service activities, including:<br>- Division 94: Activities of membership organisations<br>- Division 95: Repair of computers and personal and household goods<br>- Division 96: Other personal service activities |

Annex 3. Aggregations of NUTS 2 regions of Portugal

| Dummy variable | Dummy variable description |
|---|---|
| north | North |
| centre | Centre |
| lisbon | Lisbon Metropolitan Area |
| alentejo | Alentejo |
| algarve | Algarve |
| azores | Autonomous Region of the Azores |
| madeira | Autonomous Region of Madeira |

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