UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER THESIS

THE EFFECT OF RESEARCH AND DEVELOPMENT INVESTMENT ON FIRMS' FINANCIAL PERFORMANCE: EVIDENCE FROM EUROPEAN COMPANIES

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TABLE OF CONTENTS

LIST OF ABBREVIATIONS

R&D Research and Development

ROA Return on Assets

ROE Return on Equity

GMM Generalized Method of Moments

OLS Ordinary Least Squares

FE Fixed Effects

RE Random Effects

EU European Union

OECD Organisation for Economic Co-operation and Development

SMBs Small and Medium-sized Enterprises

ICT Information and Communication Technology

TAG Total Assets Growth

LEV Leverage

CR Current Ratio

SIZE Firm Size

RDI R&D Intensity

CAPIQ S&P Capital IQ PRO

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

1 INTRODUCTION

Investing in research and development (hereinafter R&D) is important in sustaining a firm's long-term success and, according to Bettis and Hitt (1995), serves as a means to gain and maintain competitive advantage through innovative products, improved services, and more efficient operations, ultimately affecting a company's profitability and value.

Based on the 2023 edition of the EU Industrial R&D Investment Scoreboard (European Commission, 2023), companies across various sectors within the EU have increasingly prioritized R&D investment in recent decades, as reflected in their income statements where it appears under operating expenses. This trend aligns with Europe's recent resurgence in R&D, surpassing the US in 2022 for the first time since 2015. Notably, this surge, characterized by its highest growth rate in years, primarily targets sectors such as automotive, ICT, and healthcare. Motivated by these developments, this study analyzes the impact of escalating R&D investments on the financial performance of Europe's largest companies across various industries. The decision to assess the impact of R&D investment on the financial performance of large, publicly traded companies in Europe stems from the fact that R&D expenses constitute a significant portion of European companies' total operating expenses, consequently exerting a strong influence on the bottom line. Numerous studies have investigated the influence of R&D investments on corporate results, including those by Gui-long et al. (2017), Aggelopoulos et al. (2016), and Andras and Srinivasan (2003). However, the diverse range of measurement methods, variables, and samples used in these studies limits the generalizability of findings and leads to varying conclusions regarding the impact of R&D on a company's financial performance.

While reviewing the existing literature and empirical findings on the effects of R&D expenses on profitability, a knowledge gap becomes evident in understanding how R&D investment influences the financial performance of publicly listed European companies across sectors. Existing studies often focus narrowly on specific countries, lacking a comprehensive analysis of the broader European market and its dynamic interplay over time. Furthermore, parabolic relationship between R&D activities and financial results among European companies remains unexplored, along with the identification of potential breakpoints where companies maximize profitability. Most studies concentrate solely on a linear relationship. For these reasons, this research aims to explore both linear and lagged linear relationship of R&D with business outcomes within European companies while also investigating the existence of a concave relationship. The primary objective is to determine the precise level of optimal R&D investment at which companies achieve maximum profitability.

1.1 Purpose, goal and hypotheses of the research

The purpose of this master's thesis research is to examine how R&D investments affect the profitability of companies listed on European stock markets. Additionally, it aims to identify the adequate R&D expenditures at which companies maximize their performance.

The objective is to provide empirical support for the hypotheses that suggest the existence of a linear, lagged linear, and nonlinear quadratic relationship between R&D investments and profitability. Furthermore, the research seeks to determine whether R&D investments exert a stronger effect on the financial performance of manufacturing companies compared to non-manufacturing companies, as well as high-tech companies in contrast to low-tech companies. Based on the literature review and an understanding of business dynamics, the expectation is that R&D investments in a given period may initially reduce a company's financial performance. However, a positive lagged effect of R&D investment on financial performance is anticipated over the observed period. Additionally, the study aims to confirm the presence of a bell-shaped connection between R&D investment and financial performance among Europe's largest companies, identifying the adequate amount of R&D expenditure across different sectors. Lastly, it is expected that the effects of R&D investment on profitability will be stronger for production and high-tech firms.

This research is expected to provide significant value to company management by offering insights for creating effective R&D plans and strategies. It will also be valuable to potential investors interested in companies with substantial R&D expenditures. Through analytical research, the study will offer empirical support for recommendations proposed by business leaders and academic researchers regarding the effective management of R&D expenditures. Finally, this research will serve as a foundation for future studies, which could expand the sample size and explore these effects across different sectors, comparing low versus high R&D-intensive companies and similar areas of interest.

1.2 Outline of the content

The introductory chapter provides an overview of the thesis, defining the subject, research problem, hypotheses, objectives, and the significance of the study. Following this, the literature review chapter delves into the theoretical foundations of R&D investment, including all the theories that affect the R&D. It also discusses the determinants of business performance and provides an overview of quantitative analyses of the impact of R&D activities on the company's financial results. The methodology chapter details the research methods, data collection processes, variables, and analytical models employed. The fourth chapter presents the findings through descriptiverew statistics, correlation analysis, and System Generalized Method of Moments (GMM) results on linear, lagged, and non-linear effects of R&D investment. The concluding chapter summarizes the key findings, discusess the implications and the opportunities for improving the study.

2 LITERATURE REVIEW

2.1 Research and development investment

R&D is important in measuring organizational operational effectiveness (Moncada Paternò Castello et al., 2010). Anagnostopoulou and Levis (2008) revealed that R&D activities are positively linked with abnormal returns and may improve the company's market value. Additionally, R&D is a key ingredient for many companies to gain competitive advantage. While increasing R&D expenditures does not automatically lead to improved innovation or stronger financial results, enterprises that decide to engage more in R&D activities tend to be more competitive on the market thanks to their innovation capabilities (O'Brien, 2003; Lin et al., 2006). Innovative activities carried out by companies offer consumers a broader and enhanced range of products and services. These innovations can also boost company's topline and bottom-line by designing new products and streamlining business operations processes. Such innovation is driven by investments in R&D, which is crucial for improving firm performance, as it contributes to the company's ability to develop skills and adapt to new innovation-related methods. Ho et al. (2005) states that R&D enables companies to develop new products and services tailored specifically to customer requirements.

Motivations for R&D investment arise from two broad sources: firm-specific reasons and industry-wide dynamics. On the firm-specific side, fiscal incentives and policy measures play a crucial role. Governments frequently support R&D by providing subsidies and favorable fiscal treatment, enabling companies to reduce their tax base (Chen & Li, 2018). Both Dumont (2013) and Bloom et al. (2002) find that public support measures have a positive impact on R&D activity among European companies.

From the industry-wide perspective, both competition and customer demand exert strong pressure on firms to innovate. To maintain relevance and deliver consistent value, companies must adapt quickly to changing client needs. Innovation is thus not optional but rather essential for survival and profitability (Vithessonthi & Racela, 2016). Firms that innovate faster and more effectively than their peers achieve stronger market positions. Moreover, R&D can enhance operational efficiency by streamlining processes, reducing costs, and accelerating responsiveness to customer requirements (Lee, 2020).

The company's strategy is important because it affects the amount of R&D expenditures and whether the priority will be product differentiation or business process optimization. Firms with a product differentiation strategy tend to have higher R&D expenditures. Due to the constant demand for innovation, these firms must continually invest in R&D to stay competitive, which aligns with the concept of product-oriented R&D. This approach requires constant adjustment to meet evolving market demands (Guo et al., 2018). Conversely, according to Liao and Cheung (2002), firms focusing on process-R&D typically pursue a cost leadership strategy, aiming to deliver the lowest prices by maximizing efficiency and optimizing processes, which often results in lower total R&D spendings. According to Guo et al. (2018), the relationship between R&D and company performance is positive in the context of product differentiation, while for cost leadership, it forms an inverted U-shaped curve. Chung and Choi (2017) highlight similar findings in their study among Korean firms, demonstrating that R&D has a more pronounced impact on the growth of firms with a product differentiation strategy compared to those with a cost efficiency strategy. These studies indicate that proper management of R&D is especially important for companies that adopt a product differentiation strategy.

R&D investments can be categorized into two main types based on industry in which the investment is made – basic and applied. Basic R&D encompasses experimental and theoretical efforts aimed at designing the new product (The Organisation for Economic Co-operation and Development, 2015). On the other hand, applied R&D focuses on scientific, technical, or industrial research to make future product development or enhancement smoother (Bertrand, 2009). The two forms of R&D complement each other (Henard & McFadyen, 2005). In practice, R&D can be conducted internally or outsourced to specialists or academic institutions, with outsourcing particularly beneficial for smaller businesses lacking expertise and resources. Multinational corporations often combine in-house R&D with outsourcing.

R&D activities, while essential for long-term competitiveness, also expose companies to heightened uncertainty. Compared with physical assets, knowledge-based investments are riskier because the outcomes are less predictable (Gharbi et al., 2014). Converting research spending into market-ready products often takes years, and rapid technological progress can render innovations outdated before they reach commercialization (Beladi et al., 2021). Furthermore, many new or improved products fail to achieve commercial success, and the likelihood of successful market adoption differs substantially across firms (Mansfield & Wagner, 1975). These risks are especially problematic for financial constrained companies, since higher R&D intensity is linked to greated distress probability (Zhang, 2015).

Beyond financial risks, R&D-intensive firms also struggle with a persistent knowledge gap between company's executives and capital providers. Since details of ongoing projects are rarely disclosed and their value is often absent from financial statements, external stakeholders lack the information needed to make reliable assessments (Gharbi et al., 2014; Aboody & Lev, 2002). This transparency gap complicates access to external funding, as investors hesitate to commit resources to initiatives whose prospects remain unclear. As a result, companies must weight potential growth opportunities against not only financial uncertainty but also the challenges of limited disclosure when designing their R&D strategies.

2.2 Determinants of business performance

Financial performance is a critical determinant in assessing the success of firms. The evaluation of a firm's performance encompasses three primary dimensions: productivity, profitability, and market premium (Omondi & Muturi, 2013). To achieve a comprehensive assessment, various financial performance metrics are utilized, including return on assets (ROA), return on investment (ROI), return on equity (ROE), and operating profit margin (OPM). ROA, originally introduced by Dupont in 1919, stands out as the most prevalent proxy for financial performance (Liargovas & Skandalis, 2008; Mishra et al., 2009). The foundational work in profitability analysis began with Bain (1951), who explored the relationship between profitability and structural variables such as market concentration, growth, economies of scale, and advertising. Bain's findings indicated a positive correlation between concentration and profitability, a conclusion further supported by Mann (1966). Subsequent studies by Collins and Preston (1969), Weiss (1974), and Porter (1979) showed that industry concentration had a positive effect on company's performance. In the context of the stock market, Ghosh et al. (2000) discussed the extensive use of ROA by market analysts to gauge financial performance, highlighting its effectiveness in measuring the efficiency of asset utilization in generating income. Following extensive research on the impact of R&D on company profitability, this thesis utilizes ROA and ROE as measures of financial performance. Previous research by Artz et al. (2003), Lev et al. (2005), and Sher and Yang (2005) underscores the utility of ROA in assessing a firm's profitability. Many researchers, including Vijayakumar and Devi (2011) and Delmar et al. (2013), have adopted ROA due to its ability to accurately represent a company's financial performance. ROA effectively indicates how much income is generated from the firm's assets, providing a clear picture of asset efficiency and profitability.

2.3 Past empirical studies

2.3.1 Empirical evidence on the effects of R&D investment on company performance

Research on how R&D affects firm outcomes is inconsistent, mainly because studies rely on different data sets and methodological approaches. Despite this, the general consensus is that investments in innovation generally improves company's competitiveness and financials.

Innovation tends to raise efficiency and strengthen internal results. Evidence from Agustia et al. (2020) suggests that allocating more to R&D correlates with stronger topline growth and leaner operations. Chen et al. (2019) add that these benefits materialize faster in larger firms, since they can deploy resources, such as capital and personnel skills, at scale. Similarly, Gui-long et al. (2017) highlight that companies with stronger financial positions extract above-average gains from innovation thanks to their resource buffers that help absorb risks.

The literature also connects R&D to profitability metrics. Andras & Srinivasan (2003) observed that innovation outlays supported margin expansion in consumer-focused and industrial firms, though their limited dataset constrained conclusions. Aggelopoulos et al. (2016), examining small and medium-sized firms in Greece, found that research spending boosts liquidity and cash-based returns across different industries.

R&D contributes to employment and revenue growth. Falk (2012) documented that companies in Austria with higher research commitments expanded their workforces and sales more strongly in subsequent years. Lome, Heggeseth & Moen (2016) evaluated whether innovative enterprises fared better in economic downturns. Using a dataset of industrial firms based in Norway, they concluded that those allocating substantial resources to research weathered the late-2000s financial turmoil more effectively than their peers. This suggests that investment in innovation functions as a safeguard during periods of instability as well as a driver of growth in normal conditions.

Financial markets tend to reward innovative firms even when short-term numbers decline. Studies by Lee (2020), Seo & Kim (2020), and Vithessonthi & Racela (2016) all show that firms increasing their research effort enjoy stronger market valuations, consistent with investors treating such activity as a signal of future expansion. Earlier work by Chan et al. (1990) similarly showed that companies with rising R&D budgets achieved superior share price development and higher investor returns.

Stock market persistence has also been studied. Anagnostopoulou & Levis (2008) reported that British corporations with stronger R&D engagement realized higher risk-adjusted excess returns over long horizons, while Ehie & Olibe (2010) documented improved valuations for American companies in both manufacturing and services. Ho et al. (2005) noted that in the United States, manufacturers pursuing research programs gained superior one-year market results, although this effect was not visible among service-oriented firms.

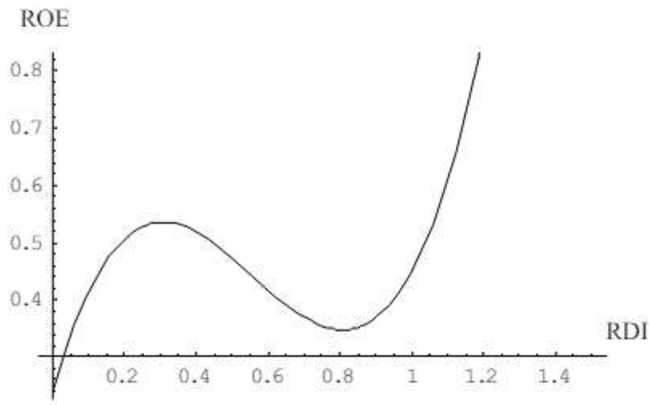
The effectiveness of innovation depends heavily on strategic context. Guo et al. (2018) showed that Chinese companies pursuing product differentiation benefited strongly, while cost-focused firms exhibited a hump-shaped link in which results improved up to a point and then fell back. Yeh et al. (2010) identified similar tipping points in asset returns, equity returns, and profit growth, with positive contributions below the cut-off but negative effects beyond it.

Other studies reveal further nonlinearities. Wang (2009, 2011) described a concave-convex curve: research enhances outcomes at low levels, erodes them at intermediate spending, and strengthens them again once budgets reach very high levels. Hartmann et al. (2006) also warned that unchecked expansion of R&D budgets can undermine profitability. Booltink & Saka-Helmhout (2018), analyzing non-high-tech European SMBs, suggested that innovation spending beyond ~10% of topline no longer delivered positive incremental results. They also noted that globally oriented SMBs must devote proportionally more resources than domestically focused peers to sustain competitiveness.

Another important aspect is that benefits often emerge with a delay. Vithessonthi & Racela (2016) found that heavy commitments initially depress operating performance in US public firms but ultimately strengthen long-term valuations, as financial markets price in expected future returns. Chen et al. (2019) likewise emphasized lag effects, suggesting that short-term losses may precede eventual benefits.

In entrepreneurial and developing contexts, results are also nuanced. Deeds (2001) concluded that consistent research engagement is crucial for wealth creation in emerging tech enterprises, with public funding particularly important in early stages. Pramod et al. (2012), analyzing production companies in India, identified a nonlinear, inverted parabolic relationship in which moderate expenditure lifted valuations but excessive spending reduced them. Lin et al. (2006) showed that R&D investments alone were insufficient to enhance firm value. They revealed a complementary effect, suggesting that strong R&D is most impactful when coupled with a focus on bringing innovations to market.

Figure 1: Concave-convex relationship (cubic regression)



Source: Wang (2011)

2.3.2 Wider oganizational outcomes of R&D investment

From the 1990s onward, researchers have devoted increasing attention to how R&D expenditures shape different organizational outcomes, though precise measurement of such effects remains challenging. Cohen et al. (1989) and De Jong et al. (2010) showed that higher R&D commitments expand a firm’s absorptive ability — meaning its capacity to identify, assimilate, and exploit outside knowledge. Put differently, firms that channel more funds into R&D frequently establish broader networks, often across greater geographical distances, which enables richer exchanges of expertise with outside partners. In the same spirit, Beise-Zee et al. (2006) found a link between innovative activity and stronger export results, suggesting that spending on innovation can bolster firms' competitive standing in international markets.

Despite these advantages, several scholars highlight potential risks. and Müller and Zimmermann (2009), Titman and Shapiro (1986), and Yasuda (2005), argued that investments in innovation generate non-physical assets that may increase a company's exposure to uncertainty. Specifically, Shapiro and Titman (1986) noted that these firms tend to experience more volatile profit streams. This volatility may, in turn, complicate access to external credit. Early-stage enterprises engaged heavily in R&D, as Müller and Zimmermann (2009) observed, often face this challenge more acutely and therefore depend disproportionately on equity-based funding. Such financing constraints may slow expansion and limit the effectiveness of innovation-driven growth strategies.

Beyond purely economic outcomes, R&D investment has also been linked to broader organizational practices. Padgett and Galan (2010), examining industrial enterprises between 1991 and 2007, observed that higher levels of R&D were associated with stronger engagement in corporate social responsibility (CSR). CSR activities generate non-physical assets such as reputational capital and stakeholder confidence, which can ensure firm's sustainable growth.

3 RESEARCH METHODOLOGY AND DATA

3.1 Research question and hypotheses development

As demonstrated in Chapter 2, higher R&D spending is associated with stronger company financial performance. The existing literature generally suggests a beneficial effect of R&D on firm performance, regardless of industry. This leads to a widely accepted notion that R&D fosters positive firm outcomes.

While previous research has shed light on the connection between R&D investment and financial performance, a critical knowledge gap persists in understanding this relationship for European publicly listed companies across all sectors. Existing studies, such as Aggelopoulos, Eriotis, Georgopoulos, and Anastasios (2016) and Falk (2010), often adopt a narrow focus, concentrating on specific European countries. This approach overlooks the potential for a more comprehensive analysis that encompasses the entire European market and captures the dynamic interplay between R&D investment and financial performance over time. Additionally, the potential for a quadratic, non-linear relationship between these variables remains largely unexplored. Current research predominantly centers on linear relationships, assuming a proportional increase in financial performance with each unit of R&D investment. This linear perspective fails to account for the possibility of diminishing returns, where exceeding a certain R&D expenditure threshold might lead to a decline in profitability due to factors such as inefficient resource allocation or delayed returns on investment.

This research aims to address these shortcomings by employing a more nuanced approach. First, it will explore the existence of both linear and lagged linear relationships between R&D investment and financial performance within European companies. Lagged relationships consider the potential time delay between R&D expenditure and its impact on financial results, acknowledging that innovation may take time to translate into tangible benefits.

Second, it will investigate the possibility of an inverse U-shaped relationship. This non-linear relationship posits that financial performance initially increases with rising R&D investment, reflecting the development of novel products and processes. However, beyond a certain optimal level of investment, additional R&D expenditure might yield diminishing returns, potentially leading to a decline in profitability. By identifying this potential breakpoint, the research could illuminate the precise level of R&D investment at which European companies achieve maximum profitability. This information would be invaluable for European businesses, enabling them to make data-driven decisions regarding R&D allocation and optimize their innovation strategies to maximize financial returns.

Ho et al. (2005) argue that a firm's capability stems from its ability to mobilize and coordinate resources to carry out specific activities — in this context, R&D. Because resources are limited, companies must allocate investments strategically to maximize the value of their key strengths. For industrial enterprises, the primary strength lies in creating innovative products, with R&D as an essential asset. Accordingly, the study presented in this thesis will assess if R&D spending has a stronger influence on the financial performance of publicly listed European manufacturing firms compared with those in non-manufacturing sectors.

As mentioned previously, a critical knowledge gap exists in understanding the relationship between R&D and public companies' performance across the entire European market, with existing research often focusing on specific countries. To address this gap, the research will employ a quantitative approach using the system Generalized Method of Moments (GMM) methodology on a panel dataset encompassing European publicly traded companies from 2013 to 2022. The underlying research questions and related hypotheses of the thesis are as follows:

[RQ1]: "How does R&D intensity without lagged effects relate to profitability of listed European companies?"

The Hypothesis 1 will provide an answer to the research question 1:

H1: Without lagged effects, R&D intensity has a negative relationship with the financial performance of listed European companies.

- H1.1: Withoug lagged effects, R&D intensity has a negative relationship with the return on assets (ROA) of listed European companies.

- H1.2: Without lagged effects, R&D intensity has a negative relationship with the return on equity (ROE) of listed European companies.

[RQ2]: “What is the impact of a previous year R&D intensity on current year profitability of listed European companies?"

The Hypothesis 2 will provide an answer to the research question 2:

H2: R&D intensity in previous year has a positive relationship with the financial performance each year of listed European companies.

- H2.1: R&D intensity in previous year has a positive relationship with the return on assets (ROA) each year of listed European companies.

- H2.2: R&D intensity in previous year has a positive relationship with the return on equity (ROE) each year of listed European companies.

[RQ3]: “Is there a concave quadratic relationship between R&D intensity and profitability for listed European companies?"

The Hypothesis 3 will provide an answer to the research question 3:

H3: There is a significant concave quadratic relationship between R&D intensity and the financial performance of listed European companies.

- H3.1: There is a significant concave quadratic relationship between R&D intensity and the return on assets (ROA) of listed European companies.

- H3.2: There is a significant concave quadratic relationship between R&D intensity and the return on assets (ROA) of listed European companies.

[RQ4]: “How does the impact of R&D investment on financial profitability differ between listed European manufacturing and non-manufacturing companies?"

The Hypothesis 4 will provide an answer to the research question 4:

H4: R&D investment has a greater impact on the financial performance of listed European manufacturing companies compared to non-manufacturing companies.

- H4.1: R&D investment has a greater impact on the return on assets (ROA) of listed European manufacturing companies compared to non-manufacturing companies.

- H4.2: R&D investment has a greater impact on the return on equity (ROE) of listed European manufacturing companies compared to non-manufacturing companies.

[RQ5]: “How does the impact of R&D investment on financial profitability differ between listed European high-tech and low-tech companies?"

The Hypothesis 5 will provide an answer to the research question 5:

H5: R&D investment has a greater impact on the financial performance of listed European high-tech companies compared to low-tech companies.

- H5.1: R&D investment has a greater impact on the return on assets (ROA) of listed European high-tech companies compared to low-tech companies.

- H5.2: R&D investment has a greater impact on the return on equity (ROE) of listed European high-tech companies compared to low-tech companies.

3.2 Research methods in past studies

In this section, an analysis of various research methods will be conducted to help answer the research question. The following paragraphs will provide a concise discussion of these methods, along with relevant studies that employed them. Finally, based on the strengths and weaknesses of each method, the most appropriate method for this study will be selected.

3.2.1 Ordinary Least Squares (OLS) regression model

Ordinary Least Squares (OLS) is a widely used method in linear regression for estimating the relationship between independent and dependent variables. It is commonly applied in panel data analysis, including pooled OLS, which is useful for analyzing data across multiple time periods. While OLS is a straightforward and broadly applicable method, it requires assumptions such as linearity, normality of residuals, absence of multicollinearity, and homoscedasticity to ensure reliable results. Pooled OLS does not account for individual effects or time-varying factors, which can lead to inefficient estimates, particularly with unbalanced data. To address this, many studies incorporate fixed or random effects models.

Several studies have employed OLS to examine the impact of R&D on firm performance. For example, Aggelopoulos et al. (2016), Vithessonthi and Racela (2016), Anagnostopoulos and Levis (2008), Ehie and Olibe (2010), and Kwon and Inui (2003) all used OLS with balanced panel data. Pramod et al. (2012) initially used pooled OLS on an unbalanced dataset but acknowledged its limitations and supplemented their analysis with additional methods to account for firm-specific effects. Gui-long et al. (2017) also employed pooled OLS but noted that this approach could lead to inefficient estimators in unbalanced data, supplementing their analysis with quantile regression. These studies highlight the broad use of OLS in R&D performance research while recognizing its limitations and the need for complementary methods in some cases.

3.2.2 Fixed-Effects and Random-Effects models

Fixed and random effects models are widely used regression techniques for panel data. The fixed effects model treats individual-specific parameters as fixed variables, controlling for unobserved heterogeneity over time by demeaning the data. This method eliminates time-invariant predictors, making it ideal for studying changes within an individual over time. The random effects model, on the other hand, assumes that individual differences are random and uncorrelated with the independent variables, allowing for the inclusion of time-invariant variables like gender. While the fixed effects model is often preferred for causal inference, the random effects model can be more efficient when its assumptions hold true. The choice between these models can be determined using the Durbin-Wu-Hausman test, which guides the selection of the appropriate model, fixed-effects or random-effects, for the dataset (Ruud, 2000).

Several studies have employed fixed and random effects models to investigate the relationship between R&D investment and firm performance. For example, Ortega-Argilés et al. (2011) used pooled OLS, fixed effects (FE), and random effects (RE) models with an unbalanced dataset from 1990-2008, finding that the FE and RE models provided more significant results than pooled OLS. Similarly, Kumbhakar et al. (2011) used unbalanced data and compared the outcomes of pooled OLS and fixed effects models. Pramod et al. (2012) also utilized both fixed and random effects methods in their analysis. These studies highlight the reliability of fixed and random effects models over pooled OLS in R&D performance research. Additionally, studies by Gardiner et al. (2009), Laird & Ware (1982), and Ramsey & Schafer (2002) offer theoretical and practical insights into the advantages and assumptions of these models, reinforcing their widespread application in causal research.

3.2.3 Generalized Method of Moments Estimation

The Generalized Method of Moments (GMM) is a statistical technique used for estimating parameters in dynamic panel data, particularly when dealing with endogeneity, heteroskedasticity, and autocorrelation. It is especially useful when there are a large number of individuals but only a few time periods. GMM can be applied in its difference or system forms, with system GMM often preferred for its higher efficiency due to the inclusion of additional instrumental variables (Roodman, 2009; Windmeijer, 2005).

Several studies have applied GMM in exploring the impact of R&D on firm performance. Jaisinghani (2016) and Sharma (2012) employed system GMM to examine the effect of R&D in the Indian pharmaceutical sector, using additional instruments to minimize bias. Similarly, Poldahl and Tingvall (2011) used system GMM to investigate R&D's influence on Swedish manufacturing firm growth. Chen et al. (2019) also applied two-step GMM to address endogeneity issues, providing more efficient and precise estimates over time. These studies highlight the efficiency of system GMM in handling bias and endogeneity.

3.2.4 Quantile regression model

Quantile regression is a regression method that estimates the relationship between independent variables and different quantiles of the dependent variable, making it useful for applications where extreme values are significant. Unlike OLS regression, which focuses on the conditional mean, quantile regression estimates various percentiles, providing a more robust measure against outliers and skewed distributions.

Several studies have employed quantile regression to analyze the relationship between R&D and firm performance. Gui-long et al. (2017) used quantile regression, finding it more appropriate than OLS because it examines the entire distribution of the dependent variable, offering a more robust indication of the impact of R&D. Falk (2010) also applied quantile regression to study R&D's effect on firm performance over time, emphasizing its utility in examining variations in the impact of R&D at different quantiles. These studies highlight quantile regression's ability to provide a nuanced understanding of the R&D-performance relationship, particularly for firms at different levels of R&D intensity.

3.2.5 Non-linear regression model

Non-linear regression is used when the relationship between the dependent and independent variables cannot be captured accurately by a linear model. This approach is particularly valuable for identifying non-linear patterns, such as U-shaped or threshold effects, which linear models may miss. Some studies have employed non-linear regression to explore the complex relationship between R&D and firm performance. Booltink and Saka-Helmhout (2017) used hierarchical multiple regression to test an inverted U-shaped impact of R&D on non-high-tech firms. Yeh et al. (2010) applied Hansen's (1999) advanced panel threshold regression model to explore threshold effects between R&D and firm performance, using balanced panel data. Wang (2011) incorporated cubic and quadratic R&D-activity variables in a non-linear regression model to test more complex relationships using balanced panel data. These studies highlight the utility of non-linear regression techniques in uncovering intricate relationships in R&D research.

3.3 Data and variables

In this research, secondary data from S&P Capital IQ PRO, a platform providing comprehensive market intelligence on global financial markets and companies, is utilized. Variables were computed using this data to test primary and related auxiliary hypotheses. The selection of variables and their indicators was based on established theory, statistical significance in prior research, and the availability of data required for calculation, aligning with methodologies from relevant studies. Only firm-level variables are considered. The names, abbreviations, and calculations of all indicator variables used for hypotheses testing can be found in Table 1 below. Depending on the model, ROA and ROE are used as dependent variables, while the following variables serve as regressors: first lags of ROA and ROE, R&D intensity, and control variables such as firm size, financial constraints, firm growth, and liquidity. Different indicators for a single variable are not considered simultaneously in a single model. The indicators of variables are defined for each firm and each observed year.

Following Roodman's (2009) recommendations, time dummies are included in all models to account for universal time-related shocks in the errors, thus preventing contemporaneous correlations across individuals. The autocorrelation test and robust estimates of coefficient standard errors assume no correlation across individuals in the idiosyncratic disturbances, with time dummies making this assumption more likely to hold. Country-dummy and sector-dummy variables are excluded from the analysis due to the employment of the two-step system GMM estimator, which inherently removes time-invariant characteristics, such as fixed effects arising from country and sector variables. The system GMM estimator helps to eliminate these fixed effects, as they do not change over time and are therefore removed during the differencing process.

Table 1: Variables and their indicators

Variable	Indicator (abbreviation)	Calculation of indicator	Relevant literature
Dependent variables			
Firm profitability	Return on assets (ROA)	ROA_t = Net $profit_t$ / Total $assets_t$	Agustia et al. (2020); Chen et al. (2019); Guo et al. (2018); Vithessonthi & Racela (2016); Yeh et al. (2010); Erdogan & Yamaltdinova (2019)
Firm profitability	Return on equity (ROE)	ROE_t = Net $profit_t$ / Total $equity_t$	Guo et al. (2018) ; Yeh et al. (2010); Erdogan & Yamaltdinova (2019)
Independent variables			
R&D investment	R&D intensity (RDI)	RDI_t = $R\&D_t$ / Total $revenue_t$	Erdogan & Yamaltdinova (2019); Vithessonthi & Racela (2016); Chen et al. (2019); Anagnostopoulou & Levis (2008)
Lagged R&D investment	Lagged R&D intensity (l.RDI)	RDI_{t-1} = R&D $expenditures_{t-1}$ / Total $revenue_{t-1}$	Chen et al. (2019); Lin (2006); Wang et al. (2011)
Squared R&D investment	Squared R&D intensity (sq_RDI)	RDI_t^2= R&D $expenditures_t^2$	Guo et al. (2018); Booltink & Saka-Helmhout (2018); Erdogan & Yamaltdinova (2019)
Firm size	Natural logarithm of total revenue (SIZE)	$SIZE_t$ = ln(Total $revenue_t$)	Chen et al. (2019)
Financial constraints	Financial leverage (LEV)	LEV_t = Total $debt_t$ / Total $assets_t$	Chen et al. (2019); Erdogan & Yamaltdinova (2019)
Firm growth	Annual growth in total assets (TAG)	TAG_t = (Total $assets_t$– Total $assets_{t-1}$) / Total $assets_{t-1}$	Chen et al. (2019)
Liquidity	Current ratio (CR)	CR_t = Current $assets_t$ / Current $liabilities_t$	Ayaydin & Karaaslan (2014)

Source: Own work based on S&P Capital IQ (2024)

3.4 Method and model specification

The effects of R&D investment on companies' financial performance will be tested using panel data methodology, due to the benefits it provides. Panel data methodology controls for individual heterogeneity, reduces issues related to multicollinearity and estimation bias, and specifies the time-varying relationship between dependent and independent variables

(Baltagi, 2005; Hsiao & Pesaran, 2002). It is crucial to include lagged values of variables in the research model as explanatory variables when examining economic and financial relationships. This is because economic and financial behavior is significantly influenced by past experiences and historical patterns, which helps avoid overestimation of parameters caused by the use of static models. As a result, the panel data model transforms into a dynamic panel data model rather than remaining static. In econometric literature, dynamic panel data analysis is grounded in the Generalized Method of Moments (GMM), first developed by Hansen in 1982. In 1991, Arellano and Bond introduced the GMM estimator for panel data to control potential endogeneity of explanatory variables. Building on this, Arellano and Bover (1995) and Blundell and Bond (1998) developed the dynamic panel GMM estimator, known as system GMM. This estimator combines a level equation and a difference equation, forming a system of regression equations in differences and levels. This approach offers improved asymptotic and finite sample properties compared to the Arellano-Bond (1991) difference GMM estimator (Ayandin & Karaaslan, 2014). The hypotheses will be tested using the system GMM estimator. There are several reasons for choosing this estimator. Firstly, it is an augmented two-step difference GMM. Secondly, it is more robust than the one-step system GMM. Thirdly, system GMM is more efficient and robust to heteroscedasticity and autocorrelation (Roodman, 2009). The model will be estimated using the GMM estimator based on the methodologies of Arellano and Bover (1995) and Blundell and Bond (1998). System GMM will allow for the control of endogeneity by utilizing instruments, making it particularly suitable for situations characterized by:

1. Few periods and many individuals,

2. A linear functional relationship, and

3. An economic and financial behaviour influenced by historical experiences and patterns, making the inclusion of lagged values of the variables in the research model crucial.

In addition, when applying the system GMM estimator, several diagnostic tests are essential to validate the model. To ensure the reliability of the results, the Arellano-Bond test for AR(1) and AR(2) in first differences will be conducted to test for serial correlation, and the Sargan-Hansen tests for overidentifying restrictions will be performed to check the validity of the instruments (Kiviet & Kripfganz, 2021). The Arellano-Bond test for AR(2) checks for second-order autocorrelation in the differenced errors, where non-rejection of the null hypothesis (p-value > 0.05) supports the validity of the instruments. The Sargan test assesses the overall validity of the instruments under the assumption of homoskedasticity, where rejection of the null hypothesis (p-value < 0.05) suggests potentially invalid instruments. The Hansen test, robust to heteroskedasticity but potentially weakened by a large number of instruments, also evaluates instrument validity. Non-rejection of the null hypothesis (p-value > 0.05) indicates valid instruments, though caution is advised when many instruments are used. These tests collectively help confirm the appropriateness of the instruments and the robustness of the model's specifications.

Based on previous studies, the following models (1) and (2) will be used to test the linear effects of R&D investment on firm performance:

$$ROA_{i,t} = \beta_0 + \beta_1 * ROA_{i,t-1} + \beta_2 * RDI_{i,t} + \beta_3 * SIZE_{i,t} + \beta_4 * LEV_{i,t} + \beta_5 * TAG_{i,t} + \beta_6 * CR_{i,t} + \varepsilon_{i,t} \quad (1.1)$$

and

$$ROE_{i,t} = \beta_0 + \beta_1 * ROE_{i,t-1} + \beta_2 * RDI_{i,t} + \beta_3 * SIZE_{i,t} + \beta_4 * LEV_{i,t} + \beta_5 * TAG_{i,t} + \beta_6 * CR_{i,t} + \varepsilon_{i,t}. \quad (2.1)$$

Furthermore, to test the lagged linear effects of R&D investment on the firm performance, the following models (3) and (4) will be used:

$$ROA_{i,t} = \beta_0 + \beta_1 * ROA_{i,t-1} + \beta_2 * RDI_{i,t} + \beta_3 * RDI_{i,t-1} + \beta_4 * SIZE_{i,t} + \beta_5 * LEV_{i,t} + \beta_6 * TAG_{i,t} + \beta_7 * CR_{i,t} + \varepsilon_{i,t} \quad (3.1)$$

and

$$ROE_{i,t} = \beta_0 + \beta_1 * ROE_{i,t-1} + \beta_2 * RDI_{i,t} + \beta_3 * RDI_{i,t-1} + \beta_4 * SIZE_{i,t} + \beta_5 * LEV_{i,t} + \beta_6 * TAG_{i,t} + \beta_7 * CR_{i,t} + \varepsilon_{i,t}. \quad (4.1)$$

In order to test the non-linear effects of R&D investment on the firm performance, the following models (5) and (6) will be used:

$$ROA_{i,t} = \beta_0 + \beta_1 * ROA_{i,t-1} + \beta_2 * RDI_{i,t} + \beta_3 * RDI^2_{i,t} + \beta_4 * SIZE_{i,t} + \beta_5 * LEV_{i,t} + \beta_6 * TAG_{i,t} + \beta_7 * CR_{i,t} + \varepsilon_{i,t} \quad (5.1)$$

and

$$ROE_{i,t} = \beta_0 + \beta_1 * ROE_{i,t-1} + \beta_2 * RDI_{i,t} + \beta_3 * RDI^2_{i,t} + \beta_4 * lnSIZE_{i,t} + \beta_5 * LEV_{i,t} + \beta_6 * TAG_{i,t} + \beta_7 * CR_{i,t} + \varepsilon_{i,t}. \quad (6.1)$$

The symbol i denotes the company, the symbol t the year, and ε symbolizes the random error. The coefficients of RDI and its squared term in models 5 and 6 allow me to determine the breakpoint of R&D intensity-profitability relation by exercising the formula: $-\beta_2 / (2*\beta_3)$, which is also used in previous studies, like in the study by Erdogan & Yamaltdinova (2019). Also, one should keep in mind that the regression coefficients generated in Stata represent the short-run effects of respective explanatory variables. To obtain the long-run effects of the explanatory variables, the following formula will be applied: $b_{j,\,long} = b_{j,\,short} * (1 / 1- \rho)$, where ρ is the estimated regression coefficient on $y_{i,\,t-1}$. This calculation will be carried out using the Stata routine *nlcom*.

3.5 Sampling procedure and research sample

As mentioned, the empirical data were drawn from S&P Capital IQ Pro platform. To study the effects of R&D expenditures on company performance, the analysis examines a 10-year period, from 2013 to 2022. For the purposes of testing Hypothesis 2 and its related auxiliary hypotheses, i.e., the lagged linear effects of R&D activity on company performance, the year 2012 was also included. To ensure accuracy, companies not listed or lacking data during the observed period were excluded. The companies in the sample are listed companies on European stock markets, specifically mid-cap and large-cap companies listed on stock markets in Germany, Turkey, Sweden, France, Switzerland, the United Kingdom, Greece, Netherlands, Denmark, Belgium, Finland, Ireland, Italy, Austria, Norway, Luxembourg, Iceland, Russia, Poland, Hungary, Slovenia, and Spain. The analysis only includes firms with consistent R&D investment reporting, which notably decreases the sample size. Many firms recognize the expenses of long-term R&D projects as a one-time charge rather than spreading them across multiple years, or they capitalize their R&D expenses, placing them on the balance sheet instead. The study began by identifying European publicly listed firms that reported R&D expenditures on an annual basis over the period 2012–2022. This screening process initially yielded 479 firms. The sample was then refined further by retaining only those companies with uninterrupted R&D disclosures for the entire observation window. Financial and accounting data, including ROA, ROE, net profit, total assets, current assets, current liabilities, total revenue, and total debt, were subsequently gathered from the S&P Capital IQ Pro platform. To ensure consistency, the dataset was constructed by selecting only firms with complete records across all variables between 2013 and 2022. The final dataset was assembled and validated using Microsoft Excel. After matching, the set of firms consisted of 438 companies, and the data sample consisted of 3 941 firm-year observations. Table 2 shows the steps and criteria of the final sample design process:

Table 2: The process of creating a sample for conducting empirical research

Criteria	**Description of the criteria**	**Number of companies**
1	**Listed companies located in Europe**	**10 455**
	- *European listed companies that lack data on R&D expenses for one or more years 2012 – 2022*	*9 976*
2	**Listed companies located in Europe that continuously publish annuall R&D expenses**	**479**
3	- *European listed companies that regularly publish R&D expenses, but lack data on ROA, ROE, Total revenue, Total debt, Total assets, Current assets, or/and Current liabilities 2013 – 2022; 2012 – 2022 (for Total revenue and Total assets)*	*41*

Final sample size:	**438**

Source: Own work based on S&P Capital IQ (2024)

Finally, using the Stata 18 software package, to mitigate the influence of present outliers, all indicators of all variables, except firm size and leverage, were winsorized at the 10th and 90th percentiles. To test hypotheses 4 and 5, as well as to perform a robustness check, the final full sample was divided into two subsamples based on the NACE Rev. 2 codes available in the S&P Capital IQ PRO database. This approach allowed for the categorization of companies into manufacturing and non-manufacturing sectors, as well as into high-tech and low-tech sectors. A similar methodology was employed by Booltink & Saka-Helmhout (2017), where the authors incorporated a dummy variable to distinguish high-tech firms from non-high-tech firms, drawing on Eurostat's NACE Rev. 2 distinction between high-tech or knowledge-intensive sectors and non-high-tech or non-knowledge-intensive sectors. Table 3 presents the categorization of companies according to the NACE codes of their respective industries.

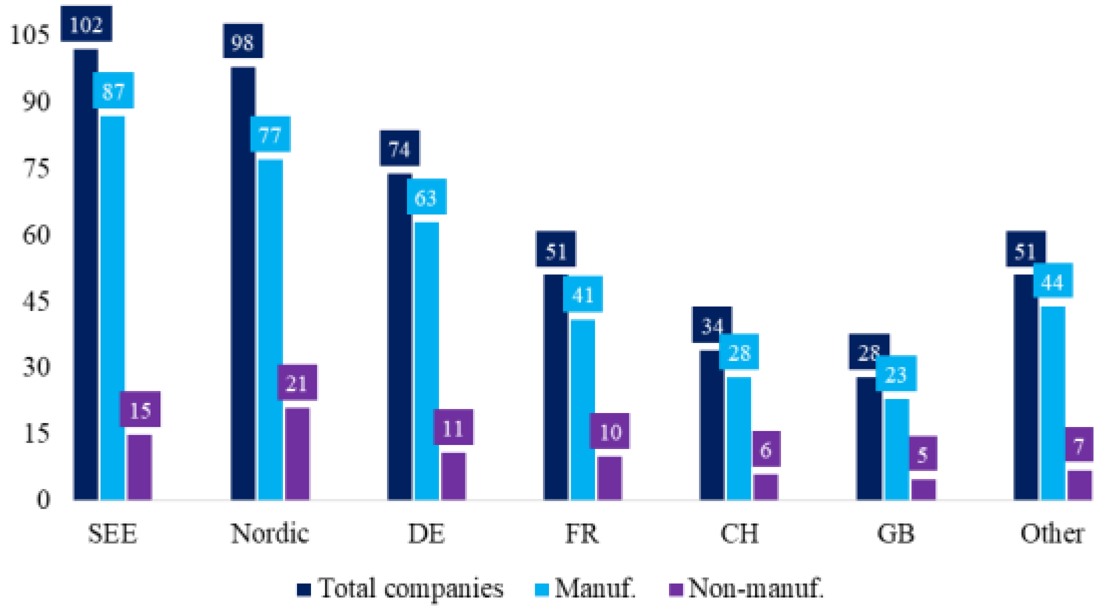
Table 3: NACE code demarcation of companies

Category	Sector	NACE code	Description
High-tech companies	Manufacturing	21, 26	High-tech industries
		20, 27-30	Medium-high-tech industries
	Services	50, 51, 58-63, 64-66, 69-75, 78, 80, 84-93	Knowledge-intensive services
Low-tech companies	Manufacturing	19, 22-25, 33	Medium-low-tech industries
		10-18, 31, 32	Low-tech industries
	Services	45-47, 49, 52, 53, 55, 56, 68, 77, 79, 81, 82, 94-96, 97-99	Less knowledge-intensive services

Source: Eurostat (2014)

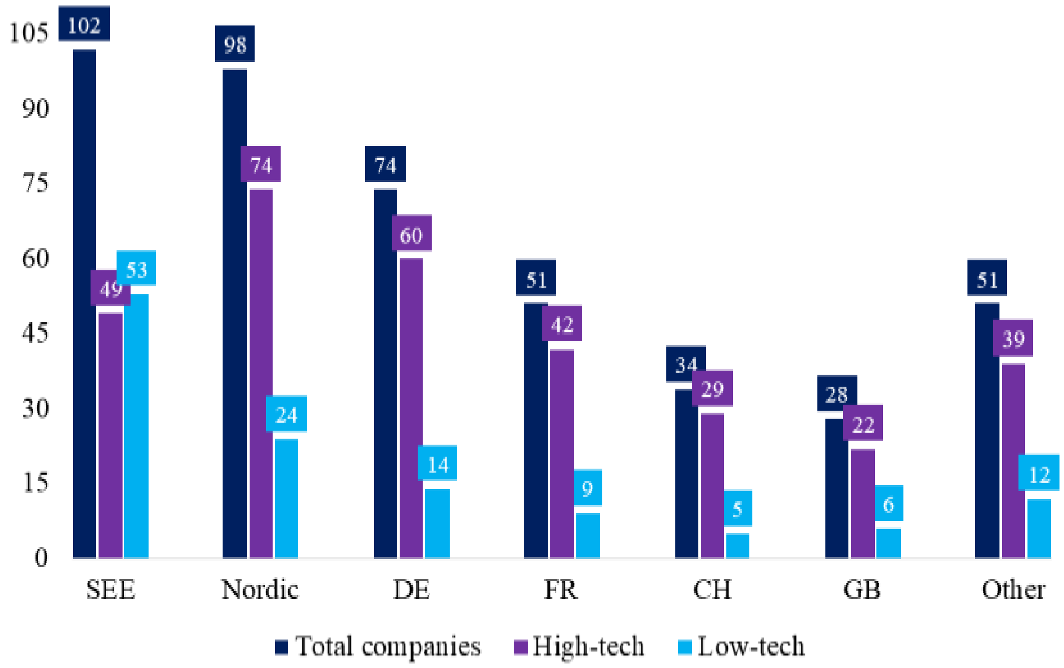
Figure 2 and Figure 3 show the distribution of companies across different countries in the sample and subsamples. As shown in Figure 2, most of the companies are coming from Southeast Europe (including Turkey, Greece, Italy, Slovenia), Nordic countries, Germany, France, Switzerland, and the UK. Additionally, Appendix 5 shows that the Health Care, Industrials, and Information Technology sectors have the highest concentration of companies in the research sample, which is not surprising since these sectors are known to be more R&D intenstive and consequently we have more companies that regularly publish their annual R&D expenses.

Figure 2: Distribution of firms across countries (manufacturing vs non-manufacturing)



Source: Own work

Figure 3: Distribution of firms across countries (incl. high-tech vs low-tech)



Source: Own work

4 RESULTS AND DISCUSSSION

This section presents the results of the panel data analysis conducted for six different models, with ROA and ROE as the dependent variables. The analysis employed the two-step system GMM estimator method. Initially, the results for the full sample, which comprises 438 companies, are discussed. This provides a comprehensive overview of the general trends and relationships observed across the entire dataset. Following this, the results for two distinct subsamples are presented. The first subsample categorizes the companies into manufacturing versus non-manufacturing sectors, allowing for a sector-specific analysis of the data.

The second subsample categorizes companies into high-tech versus low-tech industries, offering insights into the differences between technologically advanced companies and those that are less tech-focused. The section concludes with a thorough discussion of the findings, emphasizing their contributions to the existing literature and practical implications for industry practitioners and policymakers. Additionally, the limitations of the research are acknowledged, recognizing potential constraints and biases that may have impacted the results. Finally, suggestions for future research directions are provided, aiming to inspire further studies that can build on the findings presented and explore new areas of interest in the field.

4.1 Full sample results

4.1.1 Descriptive Statistics

Table 4: Descriptive Statistics – full sample

Variable	Obs	Mean	Std. dev.	Min	Max	Q1	Median	Q3
ROA	4 380	0.037	0.053	-0.077	0.1096	0.015	0.045	0.073
ROE	4 380	0.078	0.172	-0.288	0.313	0.016	0.109	0.188
RDI	4 380	0.084	0.092	0.004	0.292	0.013	0.042	0.126
l_RDI	4 380	0.084	0.094	0.004	0.297	0.127	0.042	0.127
SIZE	4 380	12.925	2.748	-0.108	19.709	11.169	13.046	14.882
LEV	4 380	0.234	0.338	0.000	12.730	0.078	0.194	0.322
TAG	4 380	0.066	0.137	-0.133	0.326	-0.033	0.049	0.144
CR	4 380	2.015	0.960	0.964	3.968	1.245	1.703	2.571

Source: Own work

Table 4 above presents the descriptive statistics of the variables used in analyzing the full sample, which includes 4380 firm-year observations. The average ROA, after winsorizing, is 3.7%, which is slightly lower but similar to the ROA of 5.6% found in the study by Erdogan and Yamaltdinova (2019), although significantly below the 15.6% ROA used in the research by Jasinghani (2016). Jasinghani (2016) employed a smaller sample, which consisted only of pharmaceutical companies, generally characterized by higher ROA and R&D intensity. The ROE shows an average value of 7.8%, which aligns with the findings from other studies. The median ROA is 4.5%, while the median ROE is slightly higher at 10.9%.

On average, companies in the sample invest approximately 8.4% of their total revenue in the development of new products (after winsorizing), with a maximum of 29.2% and a minimum of 0.4%. This average is slightly higher compared to the means reported in the studies by Guo et al. (2018) and Gui-long et al. (2017), where the values were 3.2% and 3.5%, respectively.

Given the relatively large sample that includes companies from all sectors, including capital expenditure (CAPEX) and R&D-intensive sectors, four subsamples were created: one including only manufacturing companies, another including only non-manufacturing companies, a third including companies with high technological intensity, and a fourth with companies of low technological intensity. This stratification serves as an additional robustness test, potentially revealing deeper and more interesting findings. The analyses of these subsamples are presented in the following sections.

The median average company size, measured by the natural logarithm of total revenue, is 13.05. Additionally, the median growth of companies, as measured by the year-on-year growth in total assets, is 4.9%, indicating that 50% of companies in the sample have a growth rate lower than this value, while the other 50% have a higher growth rate. The median value of the current ratio coefficient is 1.7, suggesting that companies in the sample, on average, have a strong current ratio and are able to cover their short-term liabilities with liquid assets. The median value of financial leverage, another control variable, is 19.4%.

4.1.2 Pearson Correlation Analysis

Table 5: Correlation Coefficient Matrix – full sample

	ROA	**ROE**	**RDI**	**l.RDI**	**sq_RDI**	**SIZE**	**LEV**	**TAG**	**CR**
ROA	1.000								
ROE	0.752***	1.000							
RDI	-0.500***	-0.370***	1.000						
l.RDI	-0.486***	-0.355***	0.971***	1.000					
sq_RDI	-0.555***	-0.412***	0.962***	0.930***	1.000				
SIZE	0.470***	0.392***	-0.484***	-0.485***	-0.526***	1.000			
LEV	-0.095***	0.042***	-0.058***	-0.051***	-0.028*	-0.019	1.000		
TAG	0.161***	0.201***	0.056***	0.076***	0.035**	0.025*	-0.043***	1.000	
CR	-0.044***	-0.091***	0.304***	0.306***	0.285***	-0.350***	-0.268***	0.065***	1.000

****p* < 0.05*

Source: Own work using Stata 18

Correlation analysis output of the entire dataset are presented in the Table 5 above. The correlation results show a strong inverse correlation between ROA and ROE on one side and RDI on the other side. This is the same as in the study by Chen et al. (2019) Additionally, the analysis shows that there is also a significant and negative relationship betweeen the mentioned dependent variables and lagged RDI. Although the first-order and second-order components of R&D intensity exhibit strong correlation, this does not alter the calculation of the aggregate curve. As discussed by Disatnik & Sivan (2014), multicollinearity is therefore not a concern in this case.

Furthermore, the Table 5 shows that firms' ROA ratio is inversely proportional to firm debt-to-assets ratio (leverage) and current ratio, while directly proportional to firm size and total assets growth rate. On the other hand, ROE is also directly proportional to firm size and total assets growth rate, and inversely proportional to current ratio. However, the analysis shows that financial leverage positively affects the ROE, which could mean that companies in the sample may rely heavily on debt to generate a higher net profit, thereby boosting the return on equity higher.

4.1.3 System GMM results

Table 6: Short-run effects of RDI on ROA – full sample

ROA	**Model [1]**	**Model [3]**	**Model [5]**
L.ROA	0.598*** (12.962)	0.620*** (12.470)	0.591*** (12.893)
RDI	-0.091*** (-4.980)	-0.396*** (-6.121)	0.097* (2.501)
l_RDI		0.318*** (4.512)	
sq_RDI			-0.706*** (-4.680)
SIZE	0.003*** (5.910)	0.003*** (6.200)	0.002*** (4.503)
LEV	-0.008 (-1.807)	-0.009* (-2.201)	-0.007 (-1.837)
TAG	-0.114* (-2.271)	-0.118* (-2.346)	-0.107* (-2.225)
CR	0.005*** (4.277)	0.004*** (3.945)	0.004*** (4.049)
Year Dummies	Yes	Yes	Yes
Instruments	22	23	23
Hansen test	[0.831]	[0.742]	[0.778]
Sargan test	[0.587]	[0.505]	[0.530]

AR(1)	[0.000]	[0.000]	[0.000]
AR(2)	[0.213]	[0.561]	[0.203]
Observations	3 941	3 941	3 941
Companies	438	438	438

t-statistics in parentheses
**p < 0.05; **p < 0.01; ***p < 0.001*

Source: Own work using Stata 18

Table 6 shows the results of evaluating the linear impact, lagged linear impact, and non-linear impact of R&D investment on firm's ROA. By using the model 1 for testing the linear impact of R&D investment on return on assets, the predicted coefficient of RDI variable was significant and negative at 0.1%, indicating that 1 percent increase of R&D intensity decreases the company's ROA, on average, by 0.091%. In model 3, the lagged R&D intensity variable was introduced to examine the deferred effects of R&D investment on return on assets (ROA). The results, presented in the second column of Table 6, show a positive and statistically significant relationship between lagged R&D (by 1 year) and firm profitability, as measured by ROA. Specifically, the results indicate that an increase of 1% in R&D investment in the previous year will, on average, lead to a 0.620% increase in ROA in the current year. In contrast, R&D investment in the current year negatively affects ROA.

Results for testing Hypothesis 3, and specifically auxiliary Hypothesis 3.1, are presented in the third column of Table 6 above. After using model 3 and introducing the squared R&D intensity (RDI) variable in addition to the current RDI variable, it becomes evident that both R&D intensity and its square statistically significantly affect the company's return on assets. The regression coefficients for RDI and RDI^2 are statistically significant at 5% and 0.1%, respectively. In line with expectations, the results confirm a significant concave quadratic relationship between R&D investment and company profitability, as measured by ROA. The coefficient for squared RDI is negative, while the coefficient for RDI is positive. These findings suggest that there is an optimal level of R&D intensity that maximizes the profitability of public European companies. According to the results from model 3, the optimal level of R&D expenses as a percentage of total revenue for a public European company is 6.9%. Additionally, the regression shows a significant positive relationship between firm size and ROA in all three models. On the other hand, financial leverage and firm growth significantly negatively affect a company's ROA. Lastly, the current ratio has a positive and significant relationship with ROA. In all three models, the p-values for the Hansen test and Sargan test are above 5%, indicating that the models do not suffer from over-identification issues. The p-values for AR(1) show high first-order correlation in each specification, but the p-values for AR(2) indicate no evidence of second-order correlation. These test statistics suggest proper model specification in each case, as shown in the table above. In the Table 7 below, long-run effects of RDI on ROA are analyzed.

Table 7: Long-run effects of RDI on ROA – full sample

ROA	Model [1]	Model [3]	Model [5]
RDI	-0.227*** (-6.95)	-1.041*** (-4.24)	0.237* (-2.40)
l_RDI		-0.838** (3.28)	
squared_RDI			-1.725*** (-4.76)
SIZE	0.007*** (6.10)	0.008*** (6.22)	0.006*** (4.58)
LEV		-0.023* (-2.22)	
TAG	-0.282* (-2.01)	-0.311* (-2.00)	-0.261* (-1.98)
CR	0.012*** (4.00)	0.011*** (3.74)	0.011*** (3.82)

z-statistics in parentheses
**p < 0.05; **p < 0.01; ***p < 0.001*

Source: Own work using Stata 18

As shown in Table 7, the variables that influence ROA in the short run continue to have a statistically significant relationship with the dependent variable in the long run as well. In model 1, the coefficient for R&D intensity (RDI) is negative and statistically significant at the 0.1% level, indicating that R&D investments have a negative long-run impact on a firm's ROA. Specifically, a 1% increase in RDI leads to a decrease in ROA by 0.227%, on average. This result suggests that, in the long run, R&D investment may not immediately result in profitability gains. In model 3, the lagged R&D intensity variable was included to assess the delayed effects of R&D investment on ROA. The results show that lagged RDI has a negative and statistically significant effect on ROA, meaning that R&D investments from the previous year have a negative long-term impact on ROA. Specifically, a 1% increase in lagged RDI results in a decrease in ROA by 0.838%, on average. Model 5 introduces the squared RDI variable to examine the non-linear effects of R&D investment. The coefficient for the squared RDI variable is statistically significant at the 0.1% level, indicating a concave relationship between R&D and ROA. The results show that as R&D intensity increases, the positive effects on ROA diminish. This suggests the presence of diminishing returns to R&D investment in the long run, where increasing R&D intensity beyond a certain level leads to a negative impact on profitability. Model 5 in the long run further confirms the findings from the short run, indicating that there is an optimal threshold for R&D investment, which is 6.9%. Beyond this point, additional increases in R&D intensity negatively affect profitability.

Table 8: Short-run effects of RDI on ROE – full sample

ROE	Model [2]	Model [4]	Model [6]
L.ROE	0.469***	0.475***	0.468***

	(10.343)	(10.119)	(10.291)
RDI	-0.250*** (-3.792)	-0.965*** (-4.363)	0.357* (2.242)
l_RDI		0.739** (3.029)	
sq_RDI			-2.251*** (-4.093)
SIZE	0.011*** (5.563)	0.011*** (5.790)	0.009*** (4.514)
LEV	0.017 (1.018)	0.014 (0.900)	0.020 (1.394)
TAG	-0.400 (-1.226)	-0.412 (-1.251)	-0.382 (-1.187)
CR	0.012* (2.552)	0.011* (2.409)	0.011* (2.309)
Year Dummies	Yes	Yes	Yes
Instruments	22	23	23
Hansen test	[0.810]	[0.844]	[0.813]
Sargan test	[0.643]	[0.633]	[0.642]
AR(1)	[0.000]	[0.000]	[0.000]
AR(2)	[0.534]	[0.664]	[0.642]
Observations	3 941	3 941	3 941
Companies	438	438	438

t-statistics in parentheses
**p < 0.05; **p < 0.01; ***p < 0.001*

Source: Own work using Stata 18

Table 8 shows the results of evaluating the linear impact, lagged linear impact, and non-linear impact of R&D investment on the firm's ROE. Model 2 examined the linear impact of R&D intensity (RDI) on ROE. The results showed a negative and statistically significant relationship. A 1% increase in RDI decreased ROE by 0.250% on average, indicating a larger effect on ROE compared to return on assets (ROA).

Model 4 explored the lagged effect of R&D investment. The findings revealed a positive and statistically significant relationship between lagged RDI by 1 year and ROE. A 1% increase in R&D investment in the previous year led to an increase in ROE in the current year by 0.739%, on average, ceteris paribus, while the current year's R&D investment had a negative impact.

The third model tested the hypothesis of an optimal RDI level for maximizing profitability. The results confirmed a concave quadratic relationship between RDI and ROE. The coefficient of squared RDI was negative, and RDI was positive, indicating an optimal level of RDI exists. This model estimated the optimal RDI to be 7.9% for public European companies. The study also found significant positive relationships between firm size, financial leverage, and current ratio with ROE, while firm growth had a significant negative impact.

Finally, all three models passed the Hansen and Sargan tests, indicating no over-identification issues. The presence of first-order autocorrelation was detected in all models, but no evidence of second-order correlation was found, suggesting proper model specifications. In Table 9 below, the long-run effects of RDI on ROE are analyzed.

Table 9: Long-run effects of RDI on ROE – full sample

ROE	**Model [2]**	**Model [4]**	**Model [6]**
RDI	-0.470*** (-4.48)	-1.838*** (-3.74)	0.671* (2.11)
l_RDI		1.409** (2.66)	
squared_RDI			-4.233*** (-3.87)
SIZE	0.020*** (5.22)	0.021*** (5.27)	0.016*** (4.36)
CR	0.023* (2.41)	0.021* (2.28)	0.019* (2.20)

z-statistics in parentheses
$*p < 0.05$; $**p < 0.01$; $***p < 0.001$

Source: Own work using Stata 18

As shown in Table 9, the variables that influence ROE in the short run continue to have a statistically significant relationship with the dependent variable in the long run as well. In model 1, the coefficient for RDI is negative and statistically significant at the 0.1% level, indicating that R&D investments have a negative long-run impact on a firm's ROE. Specifically, a 1% increase in RDI reduces ROE by 0.470%, on average. This result suggests that in the long run, R&D investment may not immediately lead to profitability gains.

In model 3, the lagged R&D intensity variable was included to assess the delayed effects of R&D investment on ROE. The results show that lagged RDI has a positive and statistically significant effect on ROE, meaning that R&D investments from the previous year have a positive long-term impact on ROE, with a 1% increase in lagged RDI leading to an increase in ROE by 1.409%, on average.

Model 5 in the long run confirms the thesis from the short run that there is an optimal threshold for R&D investment, which is 7.9%, beyond which further increases in R&D intensity negatively affect ROE.

4.2 Robustness tests

In empirical research, verifying the reliability and validity of results is essential to ensure accurate interpretation and robust conclusions. Robustness checks play a crucial role by testing whether findings remain consistent under different assumptions, methods, or model specifications. To confirm the reliability of the relationship between R&D investments and company performance (ROA and ROE), this study employed three robustness tests, including subsample analyses and an alternative estimation method.

The subsample analysis involved dividing the full sample of 438 firms into manufacturing vs. non-manufacturing firms and high-tech vs. low-tech firms. System GMM regressions were conducted separately on these groups to investigate whether the relationship differs across sectors or technological intensities. This approach ensures that the findings are not specific to a particular segment of the sample.

Additionally, robustness was assessed by applying a Fixed Effects (FE) model to the full sample, providing a comparison to the primary System GMM results.

4.2.1 Subsample results: manufacturing vs non-manufacturing companies

4.2.1.1 Descriptive Statistics

Table 10: Descriptive Statistics – manufacturing companies

Variable	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**	**Q1**	**Median**	**Q3**
ROA	3 630	0.041	0.050	-0.067	0.113	0.019	0.047	0.075
ROE	3 630	0.093	0.159	-0.236	0.322	0.029	0.115	0.195
RDI	3 630	0.071	0.077	0.003	0.242	0.012	0.037	0.111
l_RDI	3 630	0.071	0.077	0.003	0.243	0.012	0.037	0.110
SIZE	3 630	13.183	2.654	-0.108	19.709	11.414	13.293	15.083
LEV	3 630	0.242	0.360	0.000	12.730	0.084	0.202	0.326

TAG	3 630	0.063	0.130	-0.126	0.309	-0.032	0.048	0.136
CR	3 630	2.035	0.964	0.986	4.005	1.259	1.726	2.586

Source: Own work using Stata 18

Table 11: Descriptive Statistics – non-manufacturing companies

Variable	Obs	Mean	Std. dev.	Min	Max	Q1	Median	Q3
ROA	750	0.019	0.061	-0.107	0.098	-0.005	0.033	0.061
ROE	750	0.009	0.217	-0.463	0.250	-0.089	0.081	0.154
RDI	750	0.142	0.142	0.008	0.445	0.020	0.093	0.206
l_RDI	750	0.143	0.145	0.008	0.456	0.021	0.093	0.204
SIZE	750	11.678	2.852	0.079	17.575	9.707	11.578	13.807
LEV	750	0.199	0.199	0.000	1.689	0.051	0.157	0.296
TAG	750	0.081	0.169	-0.163	0.401	-0.043	0.062	0.186
CR	750	1.918	0.928	0.897	3.744	1.173	1.626	2.527

Source: Own work using Stata 18

In order to gain deeper insights and ensure robustness, the full sample was split into manufacturing and non-manufacturing subsamples. Table 10 and Table 11 report the summary statistics for the variables in the respective subsamples, which are used to compare the impact of research and development on the financials of manufacturing versus non-manufacturing companies.

The manufacturing subsample consists of 363 firms and 3,630 firm-year observations, while the non-manufacturing subsample consists of 75 firms and 750 firm-year observations. The larger subsample, formed of manufacturing companies (those belonging to industries with NACE Rev. 2 codes below 33, as shown in Table 3), has slightly lower average ROA and ROE. In contrast, the non-manufacturing subsample has significantly higher average R&D intensity. This is because the non-manufacturing subsample is notably smaller, with over 65% of the firms coming from the Health Care and Information Technology sectors, which are generally known for their heavy investments in R&D.

Lastly, manufacturing companies, on average, have a greater size, a higher debt-to-asset ratio, lower annual growth in total assets, and a slightly higher current ratio.

4.2.1.2 Pearson Correlation Analysis

Table 12: Pearson Correlation Matrix – manufacturing companies

	ROA	ROE	RDI	l.RDI	sq_RDI	SIZE	LEV	TAG	CR
ROA	1.000								
ROE	0.739***	1.000							
RDI	-0.483***	-0.337***	1.000						
l.RDI	-0.468***	-0.320***	0.977***	1.000					
sq_RDI	-0.546***	-0.381***	0.962***	0.936***	1.000				
SIZE	0.450***	0.363***	-0.410***	-0.410***	-0.474***	1.000			
LEV	-0.117***	0.054***	-0.024	-0.018	0.003	-0.068***	1.000		
TAG	0.154***	0.199***	0.054***	0.074***	0.030*	0.034**	-0.038**	1.000	
CR	-0.048***	-0.117***	0.318***	0.320***	0.307***	-0.379***	-0.262***	0.048***	1.000

****p < 0.05*

Source: Own work using Stata 18

Table 13: Correlation Matrix – non-manufacturing companies

	ROA	ROE	RDI	l.RDI	sq_RDI	SIZE	LEV	TAG	CR
ROA	1.000								
ROE	0.792***	1.000							
RDI	-0.433***	-0.363***	1.000						
l.RDI	-0.398***	-0.343***	0.941***	1.000					
sq_RDI	-0.488***	-0.413***	0.959***	0.895***	1.000				
SIZE	0.464***	0.408***	-0.553***	-0.551***	-0.521***	1.000			
LEV	0.035	-0.058	-0.298***	-0.297***	-0.232***	0.280***	1.000		
TAG	0.218***	0.232***	0.034	0.064*	0.008	0.024	-0.087**	1.000	

CR	-0.007	0.015	0.287***	0.294***	0.243***	-0.303***	-0.380***	0.154***	1.000

*** $p < 0.05$

Source: Own work using Stata 18

Tables 12 and 13 show the correlation coefficients of manufacturing and non-manufacturing companies, respectively. As expected due to the size of the subsample, the correlation matrix of manufacturing subsample is very similar to the correlation matrix of the full dataset which is shown in the Table 5. By examining the non-manufacturing subsample, it can be observed that the relationship between R&D intensity and firm performance is similar to that of the full sample and the manufacturing subsample.

However, the main distinction is in the financial leverage, specifically the debt-to-asset ratio. The non-manufacturing subsample, which is predominantly composed of companies from the Health Care and Information Technology sectors, does not exhibit a statistically significant relationship between financial leverage and firm profitability ratios, such as ROA and ROE.

4.2.1.3 System GMM results

Table 14: Short-run effects of RDI on ROA – manufacturing vs non-manufacturing

ROA	**Model [1]**		**Model [3]**		**Model [5]**	
	Manuf.	Non-manuf.	Manuf.	Non-manuf.	Manuf.	Non-manuf.
L.ROA	0.587***	0.340	0.699***	0.447***	0.571***	0.357
	(5.485)	(1.525)	(11.415)	(4.739)	(5.230)	(1.872)
RDI	-0.108***	-0.084*	-0.593***	-0.169**	0.135*	0.146
	(-3.235)	(-2.381)	(-7.675)	(-3.413)	(2.418)	(1.302)
l_RDI			0.530***	0.102*		
			(5.844)	(2.303)		
sq_RDI					-1.106***	-0.520
					(-3.518)	(-1.743)
SIZE	0.003***	0.004	0.003***	0.003*	0.003**	0.004
	(3.942)	(1.503)	(5.294)	(1.993)	(3.344)	(1.691)
LEV	-0.005	-0.012	-0.006	-0.008	-0.005	-0.005
	(-1.395)	(-0.430)	(-1.781)	(-0.415)	(-1.452)	(-0.258)
TAG	-0.109*	0.075	-0.151*	0.094	-0.106*	0.065

	(-1.992)	(0.626)	(-2.373)	(0.789)	(-1.966)	(0.577)
CR	0.005***	0.001	0.004***	0.001	0.005**	0.001
	(3.562)	(0.182)	(3.557)	(0.358)	(3.416)	(0.232)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	17	21	23	23	18	22
Hansen test	[0.438]	[0.178]	[0.680]	[0.687]	[0.458]	[0.297]
Sargan test	[0.130]	[0.159]	[0.369]	[0.637]	[0.151]	[0.246]
AR(1)	[0.000]	[0.038]	[0.000]	[0.000]	[0.000]	[0.012]
AR(2)	[0.443]	[0.057]	[0.852]	[0.116]	[0.468]	[0.075]
Observations	3 266	675	3 266	675	3 266	675
Companies	363	75	363	75	363	75

t-statistics in parentheses
**p < 0.05; **p < 0.01; ***p < 0.001*

Source: Own work using Stata 18

Table 14 presents the impact of R&D intensity on ROA, comparing the manufacturing subsample with the non-manufacturing subsample. In model 1, a statistically significant negative impact of R&D intensity on ROA is observed for both types of companies. Specifically, for every 1 percent increase in R&D intensity, manufacturing companies experience a 0.108 percent decrease in ROA on average. This effect is slightly weaker for non-manufacturing companies, with a decrease of 0.084%. However, the picture changes when considering the lagged effect of R&D investment in model 3. A one-year lag shows a significantly positive relationship between R&D intensity and ROA for both manufacturing and non-manufacturing companies.

Notably, the impact is stronger for manufacturing companies. A 1 percent increase in lagged R&D leads to a 0.530 percent increase in ROA for manufacturing companies, compared to a 0.102 percent increase for non-manufacturing companies. In the analysis of the optimal level of R&D investment for maximizing ROA (model 5), no clear optimal level is found for non-manufacturing companies due to the lack of statistical significance for RDI and RDI^2. However, the results suggest a breakpoint for manufacturers, with an ideal R&D intensity of 6.1%. This is slightly lower than the previously calculated breakpoint for the full sample. Overall, there is a stronger effect of R&D intensity on the ROA of manufacturing companies compared to non-manufacturing companies, which supports Hypothesis 4.1. In all models, the p-values for the Hansen test and Sargan test are above 5%, indicating that the models do not have over-identification issues. The p-values for AR(1) indicate a high first-order correlation in each specification, while the p-values for AR(2) show no evidence of second-order correlation. These test statistics confirm the proper specification of each model presented in the table

Table 15: Long-run effects of RDI on ROA – manufacturing vs non-manufacturing

ROA	**Model [1]**		**Model [3]**		**Model [5]**	
	Manuf.	Non-manuf.	Manuf.	Non-manuf.	Manuf.	Non-manuf.
RDI	-0.260***	-0.127**	-1.969***	-0.305**	0.315*	

	(-7.37)	(-3.06)	(-3.56)	(-3.27)	(2.37)	
l_RDI			1.759** (3.02)	0.185* (2.18)		
sq_RDI					-2.579*** (-4.48)	
SIZE	0.008*** (6.62)		0.009*** (5.07)	0.006* (2.32)	0.006*** (4.69)	
TAG	-0.263 (-1.67)		-0.502 (-1.82)		-0.248 (-1.66)	
CR	0.013*** (4.37)		0.014** (3.22)		0.012*** (4.10)	

z-statistics in parentheses
**p < 0.05; **p < 0.01; ***p < 0.001*

Source: Own work using Stata 18

Table 15 shows that factors affecting a company's return on assets (ROA) in the short term tend to also influence ROA in the long term, for both manufacturing and non-manufacturing firms. The one exception is firm growth (TAG), which appears to have a significant impact on short-term ROA, but not on long-term ROA.

Table 16: Short-run effects of RDI on ROE – manufacturing vs non-manufacturing

ROE	**Model [2]**		**Model [4]**		**Model [6]**	
	Manuf.	Non-manuf.	Manuf.	Non-manuf.	Manuf.	Non-manuf.
L.ROE	0.498*** (10.898)	0.381*** (3.793)	0.513*** (10.345)	0.386*** (3.765)	0.498*** (10.869)	0.382*** (3.803)
RDI	-0.246** (-3.489)	-0.319** (-2.890)	-1.433*** (-4.383)	-0.525 (-1.187)	0.365 (1.697)	0.356 (1.015)
l_RDI			1.229** (3.365)	0.214 (0.530)		
sq_RDI					-2.737** (-3.043)	-1.553 (-1.734)
SIZE	0.010*** (4.747)	0.013* (2.497)	0.010*** (4.753)	0.014* (2.253)	0.008*** (3.832)	0.013* (2.421)
LEV	0.026* (2.140)	-0.160* (-2.205)	0.023* (1.987)	-0.168* (-2.032)	0.028* (2.526)	-0.140* (-2.086)
TAG	-0.345 (-0.945)	0.097 (0.139)	-0.425 (-1.052)	-0.047 (-0.048)	-0.333 (-0.923)	-0.030 (-0.037)
CR	0.009	0.011	0.008	0.014	0.008	0.012

	(1.889)	(0.501)	(1.706)	(0.491)	(1.683)	(0.476)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	22	16	23	17	23	17
Hansen test	[0.644]	[0.217]	[0.750]	[0.222]	[0.667]	[0.234]
Sargan test	[0.345]	[0.112]	[0.444]	[0.139]	[0.363]	[0.150]
AR(1)	[0.000]	[0.000]	[0.000]	[0.006]	[0.000]	[0.001]
AR(2)	[0.169]	[0.555]	[0.292]	[0.821]	[0.162]	[0.742]
Observations	3 266	675	3 266	675	3 266	675
Companies	363	75	363	75	363	75

t-statistics in parentheses
$*p < 0.05$; $**p < 0.01$; $***p < 0.001$

Source: Own work using Stata 18

Table 16 shows the effects of R&D intensity on ROE, comparing the manufacturing subsample with non-manufacturing subsample.

Similar to the findings for ROA, the initial model (model 2) shows a negative impact of R&D intensity on ROE for both company types. In other words, for every percentage increase in R&D investment, manufacturing companies experience a 0.246% decrease in ROE on average. This effect is even stronger for non-manufacturing companies, with a decrease of 0.319%. This contradicts the previous observation where R&D had a stronger impact on manufacturers' ROA.

Furthermore, the analysis of lagged R&D investment with the model 4 reveals a crucial difference between the company types. While a one-year lag shows a positive and significant relationship between lagged R&D and ROE for manufacturers, with a 1.229% increase in ROE for every 1% increase in lagged R&D, this relationship is not statistically significant for non-manufacturing companies.

This suggests that the long-term benefits of R&D investment might materialize slower or be less pronounced for companies in non-manufacturing sectors. The analysis for optimal R&D investment (model 6) yielded no clear optimal level for either company type, due to insignificant results for both R&D intensity and its squared term.

Here, a slightly different result emerges compared to the previous analysis of the impact of R&D intensity on ROA: the current R&D investment (RDI) has a stronger direct impact on ROE for non-manufacturing companies compared to manufacturing firms. This contrasts with the findings from the ROA analysis, where current RDI had a stronger impact on manufacturing companies. However, the situation changes when considering the lagged effect. Similar to ROA, lagged R&D intensity has a stronger impact on ROE for manufacturing companies.

These findings partially support Hypothesis 4.2.

Table 17: Long-run effects of RDI on ROE – manufacturing vs non-manufacturing

ROE	Model [2]		Model [4]		Model [6]	
	Manuf.	Non-manuf.	Manuf.	Non-manuf.	Manuf.	Non-manuf.
RDI	-0.489*** (-3.99)	-0.516** (-3.21)	-2.941*** (-3.63)			
l_RDI			2.523** (2.86)			
sq_RDI					-5.447** (-2.97)	
SIZE	0.019*** (4.70)	0.020** (2.59)	0.021*** (4.47)	0.022* (2.18)	0.015*** (3.85)	0.022* (2.48)
LEV	0.052* (2.19)	-0.258* (-2.23)	0.467* (2.10)	-0.273 (-1.94)	0.056** (2.63)	-0.227* (-1.97)

z-statistics in parentheses
**p < 0.05; **p < 0.01; ***p < 0.001*

Source: Own work using Stata 18

The findings from Table 17 align with the previous analysis on return on assets (ROA). It suggests that factors influencing a company's profitability (measured by return on equity - ROE) in the short term also have a lasting impact on its profitability in the long run. This applies to both manufacturing and non-manufacturing companies. Considering the results shown in Tables 14-17, Hypothesis 4 can be accepted.

4.2.2 Subsample results: high-tech vs low-tech companies

4.2.2.1 Descriptive Statistics

Table 18: Descriptive Statistics – high-tech companies

Variable	Obs	Mean	Std. dev.	Min	Max	Q1	Median	Q3
ROA	3 150	0.030	0.063	-0.108	0.110	0.012	0.042	0.072
ROE	3 150	0.071	0.185	-0.319	0.318	0.008	0.109	0.192
RDI	3 150	0.121	0.136	0.010	0.454	0.025	0.064	0.154
l_RDI	3 150	0.122	0.139	0.010	0.461	0.025	0.063	0.155
SIZE	3 150	12.930	2.852	-0.108	19.004	11.084	13.124	15.055
LEV	3 150	0.222	0.368	0.000	12.730	0.063	0.178	0.306

TAG	3 150	0.074	0.141	-0.130	0.348	-0.027	0.055	0.153
CR	3 150	2.080	1.005	0.987	4.129	1.275	1.761	2.660

Source: Own work using Stata 18

Table 19: Descriptive Statistics – low-tech companies

Variable	Obs	Mean	Std. dev.	Min	Max	Q1	Median	Q3
ROA	1 230	0.049	0.035	-0.008	0.108	0.023	0.049	0.073
ROE	1 230	0.095	0.139	-0.197	0.302	0.036	0.112	0.181
RDI	1 230	0.028	0.037	0.001	0.113	0.003	0.009	0.033
l_RDI	1 230	0.027	0.037	0.001	0.113	0.003	0.009	0.032
SIZE	1 230	12.914	2.464	1.548	19.709	11.266	12.909	14.576
LEV	1 230	0.265	0.244	0.000	2.820	0.117	0.241	0.364
TAG	1 230	0.047	0.126	-0.135	0.279	-0.049	0.033	0.124
CR	1 230	1.847	0.829	0.900	3.465	1.195	1.566	2.394

Source: Own work using Stata 18

An additional robustness check was conducted by performing an analysis that divided the full sample of 438 European public companies into high-tech and low-tech categories, based on each company's industry code (NACE Rev. 2) as detailed in Table 3. The aim was to test Hypothesis 5, which investigates whether the impact of R&D investment on company performance differs between high-tech and low-tech firms. As shown in Tables 18 and 19, the high-tech subsample consists of 315 firms, contributing 3,150 firm-year observations. As expected, the Information Technology and Healthcare sectors dominate this group, comprising over 56% of the firms in these sectors for the entire sample. In contrast, the low-tech subsample consists of 123 firms, providing 1,230 firm-year observations, with the most prominent industries being Industrials, Consumer Discretionary, and Materials. One initial observation is the difference in profitability between the two groups. Low-tech companies generally exhibit higher return on assets (ROA) and return on equity (ROE) compared to their high-tech counterparts. As expected, high-tech companies allocate a larger portion of their resources to R&D, reflected in their significantly higher average R&D intensity. This is consistent with the nature of these industries, where innovation plays a crucial role in success. High-tech companies also tend to have less leverage, higher growth, and a higher current ratio on average.

4.2.2.2 Pearson Correlation Analysis

Table 20: Correlation Matrix – high-tech companies

	ROA	ROE	RDI	l.RDI	sq_RDI	SIZE	LEV	TAG	CR
ROA	1.000								
ROE	0.764***	1.000							
RDI	-0.640***	-0.471***	1.000						
l.RDI	-0.615***	-0.448***	0.958***	1.000					
sq_RDI	-0.671***	-0.490***	0.965***	0.919***	1.000				
SIZE	0.544***	0.425***	-0.588***	-0.586***	-0.591***	1.000			
LEV	-0.111***	0.074***	-0.006	0.003	0.014	-0.038**	1.000		
TAG	0.148***	0.190***	0.026	0.053***	0.012	-0.008	-0.053***	1.000	
CR	-0.119***	-0.148***	0.336***	0.339***	0.308***	-0.380***	-0.228***	0.093***	1.000

****p < 0.05*

Source: Own work using Stata 18

Table 21: Correlation Matrix – low-tech companies

	ROA	ROE	RDI	l.RDI	sq_RDI	SIZE	LEV	TAG	CR
ROA	1.000								
ROE	0.691***	1.000							
RDI	-0.107***	-0.138***	1.000						
l.RDI	-0.098***	-0.136***	0.989***	1.000					
sq_RDI	-0.111***	-0.145***	0.974***	0.963***	1.000				
SIZE	0.203***	0.283***	-0.275***	-0.278***	-0.309***	1.000			
LEV	-0.088***	-0.105***	-0.142***	-0.142***	-0.141***	0.065**	1.000		
TAG	0.197***	0.228***	0.102***	0.115***	0.097***	0.107***	0.007	1.000	

CR	0.177***	0.084***	0.148***	0.146***	0.151***	-0.257***	-0.424***	-0.020	1.000

****$p < 0.05$*

Source: Own work using Stata 18

Tables 20 and 21 present the correlation coefficients for high-tech and low-tech companies, respectively. A closer examination of the coefficients for both the high-tech and low-tech subsamples reveals some interesting patterns. In both groups, R&D intensity and firm size are negatively correlated with return on assets (ROA) and return on equity (ROE). However, the negative impacts are significantly stronger for high-tech companies. This suggests that high-tech firms may experience larger changes in profitability due to R&D investments and their size.

The relationship between financial leverage and profitability presents a mixed picture. While financial leverage negatively impacts ROA for both subsamples, it interestingly shows a positive influence on ROE for high-tech companies, whereas it has a negative impact on ROE for low-tech companies. This could indicate that high-tech companies leverage debt to capitalize on future growth potential, which may boost ROE as long as the debt remains manageable.

Current ratio also behaves differently between the two groups. For high-tech firms, a higher current ratio (indicating greater short-term liquidity) is associated with lower profitability (ROA and ROE). Conversely, for low-tech companies, a higher current ratio translates to a positive impact on profitability. This unexpected finding warrants further exploration. Overall, the subsample analysis underscores the differing impact of various factors on profitability between high-tech and low-tech companies. These insights suggest that a one-size-fits-all approach may not be entirely suitable when considering R&D investment and financial strategies for firms in different sectors.

4.2.2.3 System GMM results

Table 22: Short-run effects of RDI on ROA – high-tech vs low-tech

ROA	**Model [1]**		**Model [3]**		**Model [5]**	
	High-tech	Low-tech	High-tech	Low-tech	High-tech	Low-tech
L.ROA	0.604*** (9.369)	0.882*** (2.923)	0.638*** (9.887)	0.963*** (2.809)	0.563*** (5.047)	0.866*** (2.933)
RDI	-0.104*** (-5.482)	-0.081 (-1.576)	-0.311*** (-6.486)	-0.488 (-1.845)	0.051 (1.577)	-0.168 (-1.797)
l_RDI			0.227*** (4.240)	0.428 (1.350)		
sq_RDI					-0.374*** (-4.075)	0.786 (0.849)

SIZE	0.002*** (3.551)	-0.000 (-0.284)	0.002*** (3.858)	-0.000 (-0.315)	0.002* (2.527)	-0.000 (-0.156)
LEV	-0.011* (-2.183)	-0.007 (-0.688)	-0.011* (-2.495)	-0.005 (-0.554)	-0.010** (-2.896)	-0.007 (-0.690)
TAG	-0.098 (-1.767)	0.090 (0.895)	-0.090 (-1.709)	0.061 (0.519)	-0.115 (-1.855)	0.091 (0.908)
CR	0.005** (3.493)	0.001 (0.430)	0.004** (3.002)	0.001 (0.188)	0.005** (3.045)	0.002 (0.483)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	22	19	23	20	18	20
Hansen test	[0.835]	[0.301]	[0.703]	[0.319]	[0.577]	[0.292]
Sargan test	[0.551]	[0.170]	[0.223]	[0.166]	[0.451]	[0.166]
AR(1)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
AR(2)	[0.515]	[0.158]	[0.865]	[0.239]	[0.513]	[0.148]
Observations	2 834	1 107	2 834	1 107	2 834	1 107
Companies	315	123	315	123	315	123

t-statistics in parentheses
$*p < 0.05$; $**p < 0.01$; $***p < 0.001$

Source: Own work using Stata 18

Table 22 shows the effects of R&D intensity on ROA, comparing the high-tech subsample with the low-tech subsample.

In models 1 and 2, the results show no statistically significant relationship between R&D intensity (RDI) and ROA for low-tech companies. This suggests that R&D investments might not have a clear short-term impact on profitability for firms in low-tech industries. On the other hand, the results for high-tech companies reveal a different pattern. Model 1 shows a significant negative relationship between current RDI and ROA, indicating that higher R&D investment may lead to a decrease in short-term profitability for high-tech firms. However, when lagged RDI (i.e., the impact of R&D from the previous year) is introduced in model 2, the relationship turns positive and significant. This suggests that the benefits of R&D investment for high-tech companies might materialize in the long term, potentially leading to higher ROA.

The analysis for the optimal R&D level (model 5) was inconclusive for both high-tech and low-tech companies. This is because the coefficients for both current RDI and its squared term were not statistically significant. These results support Hypothesis 5.1, which posits that the impact of R&D intensity on ROA differs between high-tech and low-tech companies. The analysis suggests that R&D has a stronger and more complex relationship with ROA for high-tech firms. While it may lead to a short-term decrease in profitability, the long-term benefits appear to be more pronounced. For low-tech companies, the connection between R&D and ROA seems less clear and warrants further investigation. To ensure the robustness of the findings, statistical tests were performed to verify the validity of the models. These tests confirmed that the models are appropriate for the data and that there are no major concerns with how the errors are distributed within the models.

Table 23: Long-run effects of RDI on ROA – high-tech vs low-tech

ROA	Model [1]		Model [3]		Model [5]	
	High-tech	Low-tech	High-tech	Low-tech	High-tech	Low-tech
RDI	-0.261*** (-9.07)		-0.859*** (-3.75)			
l_RDI			0.627** (2.74)			
sq_RDI					-0.857*** (-4.64)	
SIZE	0.006*** (4.15)		0.007*** (4.57)		0.005*** (3.72)	
LEV	-0.027* (-2.24)		-0.030* (-2.51)		-0.022** (-2.92)	
CR	0.012** (3.05)		0.100** (2.75)		0.011** (3.09)	

z-statistics in parentheses
**p < 0.05; **p < 0.01; ***p < 0.001*

Source: Own work using Stata 18

As observed in Table 23, the factors affecting a company's return on assets (ROA) exhibit similar short-term and long-term influences for both high-tech and low-tech firms.

Table 24: Short-run effects of RDI on ROE – high-tech vs low-tech

ROE	Model [2]		Model [4]		Model [6]	
	High-tech	Low-tech	High-tech	Low-tech	High-tech	Low-tech
L.ROE	0.463*** (9.313)	0.382*** (3.903)	0.470*** (8.857)	0.507*** (1.952)	0.572*** (6.487)	0.381*** (3.920)
RDI	-0.275*** (-5.658)	-0.820*** (-2.300)	-0.640*** (-4.644)	-0.674 (-0.334)	0.061 (0.667)	-0.393 (-0.613)
l_RDI			0.386** (2.704)	0.431 (0.177)		
sq_RDI					-0.653** (-2.793)	-3.853 (-0.643)
SIZE	0.008*** (4.229)	-0.001 (-0.209)	0.009*** (4.518)	0.007 (1.072)	0.006** (2.714)	-0.002 (-0.232)
LEV	0.026 (1.940)	-0.053 (-1.253)	0.022 (1.690)	-0.021 (-0.479)	0.025* (2.089)	-0.053 (-1.266)
TAG	-0.152 (-0.598)	1.524 (1.782)	-0.139 (-0.530)	0.077 (0.072)	-0.084 (-0.276)	1.503 (1.796)
CR	0.010	0.014	0.008	0.010	0.006	0.014

	(1.796)	(1.711)	(1.626)	(0.974)	(1.031)	(1.707)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	22	22	23	18	23	23
Hansen test	[0.943]	[0.456]	[0.897]	[0.195]	[0.898]	[0.445]
Sargan test	[0.872]	[0.342]	[0.795]	[0.081]	[0.848]	[0.325]
AR(1)	[0.000]	[0.032]	[0.000]	[0.014]	[0.000]	[0.029]
AR(2)	[0.544]	[0.368]	[0.439]	[0.564]	[0.430]	[0.371]
Observations	2 834	1 107	2 834	1 107	2 834	1 107
Companies	315	123	315	123	315	123

t-statistics in parentheses
**p < 0.05; **p < 0.01; ***p < 0.001*

Source: Own work using Stata 18

Table 24 shows the effects of R&D intensity on ROE, comparing the high-tech subsample with low-tech subsample.

Looking at model 2, both groups experience a significant negative impact of R&D intensity on ROE. In simpler terms, for every 1% increase in R&D investment, high-tech companies see their ROE decrease by 0.275% on average, while the effect is even stronger for low-tech companies with a decrease of 0.820%.

Furthermore, the analysis of lagged R&D investment with the model 4 reveals a crucial difference between the company types. While a one-year lag shows a positive and significant relationship between lagged R&D and ROE for high-tech firms (with a 0.386 percent increase in ROE for every percentage increase in lagged R&D), this relationship is not statistically significant for low-tech companies.

The analysis for optimal R&D investment (model 6) yielded no clear optimal level for either company type, due to insignificant results for both R&D intensity and its squared term.

Table 25: Long-run effects of RDI on ROE – high-tech vs low-tech

ROE	**Model [2]**		**Model [4]**		**Model [6]**	
	High-tech	Low-tech	High-tech	Low-tech	High-tech	Low-tech
RDI	-0,512*** (-6,47)	-1,325* (-2,01)	-1,208*** (-3,88)			
l_RDI			0,728* (2,38)			
sq_RDI					-1,524** (-3,03)	
SIZE	0,016*** (4,38)		0,166*** (4,60)		0,013*** (3,55)	
LEV					0,059* (2,21)	

z-statistics in parentheses
**p < 0.05; **p < 0.01; ***p < 0.001*

Source: Own work using Stata 18

As observed in Table 25, the factors affecting a company's ROE exhibit similar short-term and long-term effects for both high-tech and low-tech firms.

4.2.3 Fixed effects model

This study employs a Fixed Effects (FE) model to control for unobserved firm-specific characteristics, such as industry norms and regional economic conditions, which are likely correlated with key variables like R&D intensity, size, and leverage. Fixed Effects focus on within-company variations over time, ensuring that time-invariant heterogeneity does not bias the results.

To formally assess whether Random Effects (RE) might also be appropriate, the Hausman test was conducted. The test evaluates whether unique errors are correlated with the regressors. Based on the results, the Fixed Effects model was selected as the preferred approach, based on the results of the Hasuman test shown in Table 26 below. By employing these methods, the study ensures the stability and reliability of its results, strengthening the credibility of the overall analysis.

Table 26: Hausman test results

Variables	**Fixed (b)**	**Random (B)**	**Difference (b-B)**
RDI	-0.563	-0.179	-0.384
l_RDI	0.007	0.025	-0.018
sq_RDI	0.720	-0.338	1.058
SIZE	0.010	0.007	0.003
LEV	-0.002	-0.003	0.001
TAG	0.028	0.342	-0.006

CR	0.004	0.005	-0.001
Chi square test	Chi2 (7) = 102.59		
Prob>chi2	0.0000		

Source: Own work using Stata 18

The results of the Hausman test in Table 26 strongly support the use of FE model. Thi Chi-square statistics with a p-value of less than 5% indicates a significant correlation between unique errors and the regressors, rejecting the null hypothesis that favors RE. These results confirm that the FE model is more appropriate for controlling unobserved firm-specific effects and ensuring robust estimates.

Below in Table 27 is the robustness test analysis of the impact of R&D investment on profitability using FE model.

Table 27: Effects of RDI on ROA – full sample – results of FE model

	ROA			**ROE**		
	Model [1]	**Model [3]**	**Model [5]**	**Model [2]**	**Model [4]**	**Model [6]**
Constant	-0.713*** (-5.620)	-0.116*** (-9.130)	-0.063*** (-4.950)	-0.123* (-2.190)	-0.126*** (-2.240)	-0.098* (-2.740)
RDI	-0.319*** (-16.100)	-0.321*** (-14.210)	-0.558*** (-9.090)	-0.663*** (-7.560)	-0.692*** (-6.930)	-1.393*** (-5.130)
l_RDI		0.003 (3.170)			0.055 (4.620)	
sq_RDI			0.718*** (4.120)			2.190*** (2.840)
SIZE	0.009*** (10.480)	0.009*** (10.480)	0.009*** (10.590)	0.017*** (4.230)	0.174*** (4.25)	0.0176*** (4.290)

LEV	-0.002 (-1.580)	-0.003 (-1.580)	-0.002 (-1.450)	0.043*** (6.110)	0.043*** (6.100)	0.044*** (6.200)
TAG	0.030*** (9.150)	0.029*** (9.120)	0.028*** (8.970)	0.187*** (13.260)	0.186*** (13.210)	0.185*** (13.130)
CR	0.004*** (4.850)	0.004*** (4.850)	0.004*** (4.790)	0.005 (1.340)	0.005 (1.340)	0.005 (1.300)
Rho	0.689	0.689	0.721	0.459	0.456	0.493
R-squared within	0.147	0.143	0.147	0.081	0.082	0.837
F test: u_i=0	F(437. 3936) = 17.10***	F(437. 3935) = 17.10***	F(437. 3935) = 15.81***	F(437. 3936) = 8.00***	F(437. 3935) = 8.00***	F(437. 3935) = 7.630***
F test: model fitness	F(5. 3936) = 131.39***	F(6. 3935) = 109.47***	F(6. 3935) = 112.76***	F(5. 3936) = 70.15***	F(6. 3935) = 58.51***	F(6. 3935) = 59.91***
Obs.	4 379	4 379	4 379	4 379	4 379	4 379
Companies	438	438	438	438	438	438

t-statistics in parentheses
**p < 0.05; **p < 0.01; ***p < 0.001*

Source: Own work using Stata 18

The FE models from the Table 27 above reveal a complex relationship between R&D investment and financial performance, characterized by predominantly negative immediate effects. Across ROA and ROE models, R&D investment consistently demonstrates significant negative coefficients ranging from -0.319 to -1.393, suggesting that increased R&D expenditures initially correlate with reduced financial returns.

The impact becomes more apparent when examining the nonlinear dynamics, with squared RDI terms revealing an inverted U-shaped relationship. Positive squared coefficients (0.718 for ROA and 2.190 for ROE) indicate an optimal R&D investment threshold, beyond which returns begin to improve, challenging the simplistic linear interpretation of innovation investments. Lagged R&D investments have insignificant effect based on the FE models 3 and 4. Across all models examined, firm size exhibited a significant positive correlation with financial profitability. This effect was particularly pronounced on ROE. Financial leverage demonstrated a significant positive impact exclusively on ROE, suggesting that increased debt-to-asset ratios, on average, lead to higher ROE within the sample. Conversely, while the current ratio significantly and positively influenced ROA, its impact on ROE was statistically insignificant.

5 CONCLUSION

5.1 Overall findings

This thesis explores the effects of R&D investment on the financials of publicly held European corporations, covering all sectors for the period 2013–2022. Previous research on R&D and its effect on profitability in Europe has often been limited in scope. Many studies focused on specific countries, failing to provide a comprehensive view for all listed European companies. Furthermore, previous analyses have tended to be static, lacking the ability to examine the dynamic effects of R&D investment over time. There is also a notable absence of studies specifically targeting public European companies. Additionally, no prior research has explored the most effective level of R&D investment needed to maximize profitability across the entire European market. The sectoral and industrial scope of past studies has been limited, affecting the generalizability of their findings. While some research has acknowledged differences between high-tech/low-tech and manufacturing/non-manufacturing companies, these studies have not provided a comprehensive sectoral or industrial scope.

To address these gaps, this research offers a novel perspective by examining the impact of R&D investment on both short-term and long-term profitability (measured by ROA and ROE) across the entire European market of listed companies. This analysis considers overall trends while also exploring sector-specific dynamics by presenting separate results for high-tech versus low-tech and manufacturing versus non-manufacturing companies. By doing so, this research provides a more comprehensive understanding of the complex relationship between R&D investment and its impact on listed European companies' profitability.

The research finds a significant negative impact of R&D investments on the financial profitability of listed European companies during 2013–2022, supporting Hypothesis 1. This finding aligns with Chen et al. (2019), who studied the effects of R&D investment on the profitability of Taiwanese semiconductor companies using the system GMM method, and Vithessonthi and Racela (2016), who investigated non-financial companies listed on the U.S. stock market from 1990 to 2013. This negative relationship can be explained by the fact that R&D expenses are typically classified as operating expenses (OPEX) in the income statements of the companies, which increases OPEX and lowers net profit for the period. The study also confirms Hypothesis 2, which posits a statistically significant positive one-year lagged effect of R&D investment on the profitability of listed European companies. This indicates that the companies experience a positive deferred impact, with R&D expenditures enhancing business performance in the following year. This finding aligns with several empirical studies, including those by Chen et al. (2019), Sougiannis (1994), and Lin (2006). Notably, this positive one-year lagged effect of R&D investment on ROA and ROE is confirmed using the system GMM method, even though the robustness tests employing fixed effects (FE) method do not show significant results for lagged effects. The system

GMM method is particularly suited for this analysis due to its ability to address endogeneity, which is a common issue when studying the relationship between R&D and profitability. Endogeneity arises because R&D investment decisions are influenced by past and expected future performance, making traditional estimation methods less reliable. The system GMM method addresses this by using lagged dependent and independent variables as instruments, effectively capturing the dynamic nature of the relationship and mitigating bias caused by omitted variable issues and simultaneity. In contrast, the FE model does not adequately address these dynamic endogeneity concerns, as it does not use lagged variables as instruments. Therefore, the system GMM results are considered more accurate and robust for capturing the deferred impact of R&D investments, supporting the hypothesis despite the lack of significance in the FE model results.

Additionally, the study supports the findings of Wang (2011), Erdogan and Yamaltdinova (2019), Yeh (2010), and Guo et al. (2018) regarding the non-linear, concave quadratic relationship between R&D investments and financial performance. Specifically, the study shows that R&D intensity initially increases profitability for listed European companies, but as R&D expenditures continue to rise, the returns on assets and equity decrease. The research identifies optimal thresholds for R&D expenditure to maximize financial performance: approximately 6.9% of total revenue for maximizing ROA and 7.9% for maximizing ROE. These findings suggest that while R&D investment is beneficial up to a certain point, exceeding these thresholds may lead to reduced profitability metrics, thereby supporting Hypothesis 3.

In addition to the primary analysis, robustness checks were conducted to ensure the validity of the findings. The first robustness check involved splitting the sample into manufacturing and non-manufacturing subsamples to test Hypothesis 4, which posits that R&D investment has a stronger impact on the profitability of listed manufacturing firms compared to non-manufacturing firms. The results confirm that R&D investment indeed has a more significant positive effect on the profitability of manufacturing companies. This finding supports Ho et al. (2005), who argue that manufacturing firms benefit significantly from R&D investments, fostering innovation and competitive product development, unlike non-manufacturing firms, which may benefit more from investments in marketing and advertising.

The second robustness check involved splitting the full sample into high-tech and low-tech firm subsamples to test Hypothesis 5, which suggests that high-tech companies experience a greater impact of R&D investment on profitability. The results of this analysis across the two subsamples align with the findings of Ortega-Argiles et al. (2011), showing that coefficients for high-tech sectors are significantly larger compared to those in non-high-tech sectors. This suggests that firms in high-tech sectors are better at translating R&D investment into productivity gains.

To further validate these findings, additional robustness tests using the fixed effects (FE) model were performed. The FE models reveal a complex relationship between R&D investment and financial performance, characterized by predominantly negative immediate effects. In both ROA and ROE models, R&D investment consistently shows significant negative coefficients ranging from -0.319 to -1.393, suggesting that increased R&D expenditures initially correlate with reduced financial returns. The nonlinear dynamics become more apparent when examining the squared RDI terms, which reveal an inverted U-shaped relationship. Positive squared coefficients (0.718 for ROA and 2.190 for ROE) suggest an optimal R&D investment threshold, beyond which returns begin to improve, challenging a simplistic linear interpretation of innovation investments. However, lagged R&D investments show insignificant effects based on the FE models, in contrast to the results obtained using the system GMM method.

These additional results reaffirm the primary conclusions of this research while offering further insights into the complexities of R&D investment and financial performance in listed European companies. The system GMM method, by addressing dynamic endogeneity, remains a more reliable approach for capturing the long-term effects of R&D investments, including the one-year lagged impact, which supports the hypothesis that R&D expenditures enhance profitability over time.

Table 28: Conclusions based on research questions

Research question	**Conclusion drawn**
[RQ1] How does R&D intensity without lagged effects relate to profitability of listed European companies?	R&D intensity significantly reduces ROA and ROE of observed firms.
[RQ2] What is the impact of a previous year R&D intensity on current year profitability of listed European companies?	R&D intensity has significantly positive one-year lagged effect on ROA and ROE of observed firms.

[RQ3] Is there a concave quadratic relationship between R&D intensity and profitability for listed European companies??	Yes, there is a statistically significant breakpoint in the relationship between R&D intensity and profitability.
[RQ4] How does the impact of R&D investment on financial profitability differ between listed European manufacturing and non-manufacturing companies?	There is a stronger impact of R&D investment on the profitability of listed manufacturing firms.
[RQ5] How does the impact of R&D investment on financial profitability differ between listed European high-tech and low-tech companies?	There is a stronger impact of R&D investment on the profitability of listed high-tech firms.

Source: Own work

5.2 Research contributions and implications

In this thesis, the impact of R&D investment on the financial profitability of listed European companies was examined. The analysis took into account sector and industry characteristics, as well as each firm's core business within the sample. Specifically, the effects of R&D investment were explored in the context of manufacturing versus non-manufacturing firms, and high-tech versus low-tech firms. The findings indicate that R&D investment has a stronger impact on the profitability of manufacturing and high-tech firms.

This research contributes valuable insights into the relationship between R&D investment (measured through R&D intensity) and the profitability of listed European companies. It reveals that R&D investment in a given period may initially reduce profitability but can positively influence it in subsequent years, suggesting a positive and lagged effect of R&D investments on performance. Furthermore, the study identifies a non-linear, concave quadratic, inverse U-shaped relationship between R&D intensity and profitability. The results suggest that managers seeking to maximize profitability should aim to maintain R&D intensity near optimal levels and avoid deviations. Additionally, this study deepens the understanding of the importance of effective R&D spending management and highlights the presence of lagged effects from R&D investments. Therefore, it is advisable for firms to anticipate positive impacts from R&D investments that may not manifest immediately within the same year.

5.3 Limits of the research and future proposition

This study recognizes couple of limitations. First, the dataset includes 438 companies across multiple sectors and marketplaces. While the breadth offers a general overview, a narrower focus on a single sector or industry could generate more precise insights. Second, the sample is not fully representative because firms from highly developed European companies are overrepresented. Past studies show that country-specific factors, such as regulatory frameworks, incluence R&D success, which means the results may not apply equally across all marketplaces. Third, the analysis is restricted to publicly listed corporations, excluding firms not listed on stock markets. This limits the scope of inference, since private enterprises may follow different strategies in financing and innovation.

Consequently, these limitations represent opportunities for future analyses. For example, expanding beyond Europe to include firms in the U.S. and Asia, where R&D spending has been accelerating, would allow to test how different institutional and regulatory environments impact companies' investments in innovation. Another opportunity to dive deep into this topic is to analyze how the disruptions in investments cycles and supply chains driven by worlwide pandemic caused by coronavirus affected companies' R&D strategies and financials – an expectation is that high-growth firms (for instance: technology, e-commerce, healthcare companies) sustained or expanded their R&D investments, while companies in sectors like hospitality, tourism, aviation, traditional retail reduced their investments in innovations.

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APPENDICES

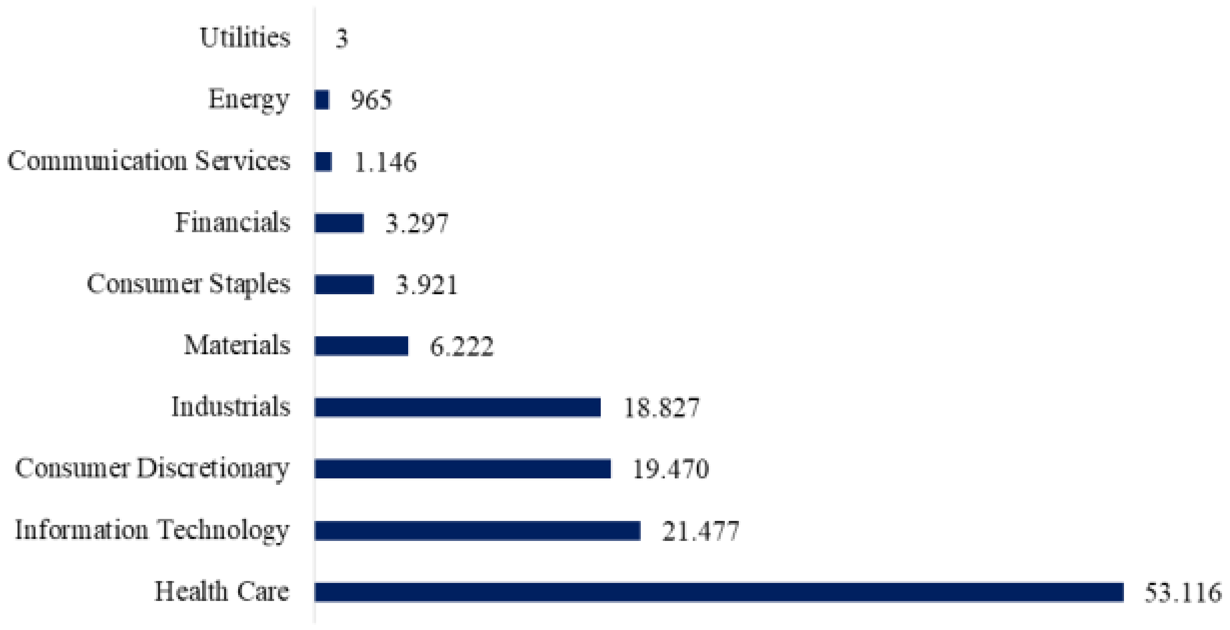
Appendix 1: Summary in Slovene language

Raziskave in razvoj (R&D) sta ključna dejavnika za spodbujanje inovacij, tehnološkega napredka in trajnostne rasti podjetij v sodobnem, dinamičnem gospodarskem okolju. Namen te magistrske naloge je podrobno raziskati vpliv intenzivnosti vlaganj v R&D na finančno uspešnost podjetij, s posebnim poudarkom na razlikah med industrijskimi panogami in velikostjo podjetij. Za analizo smo uporabili empirični pristop, ki temelji na panelnih podatkih podjetij, pri čemer smo uporabili napredne ekonometrične metode, vključno s sistemskim in diferenčnim GMM ter modeli fiksnih učinkov, da bi preučili dinamične učinke vlaganj v R&D na ključne finančne kazalnike, kot so donosnost sredstev (ROA), donosnost kapitala (ROE) in rast podjetij.

Rezultati raziskave kažejo, da intenzivnost vlaganj v R&D pozitivno in statistično značilno vpliva na finančno uspešnost podjetij. Vendar se ta vpliv razlikuje glede na velikost podjetja in industrijsko panogo, v kateri podjetje deluje. Večja podjetja in podjetja v visokotehnoloških sektorjih beležijo močnejše pozitivne učinke vlaganj v R&D, medtem ko manjša podjetja pogosto omejujejo finančne zmogljivosti in negotovi denarni tokovi, kar lahko zmanjša učinkovitost R&D aktivnosti. Poleg tega naloga poudarja pomen strateškega finančnega upravljanja in načrtovanja R&D projektov kot ključnih dejavnikov za povečanje konkurenčnosti, inovativnosti in dolgoročne trajnosti podjetij.

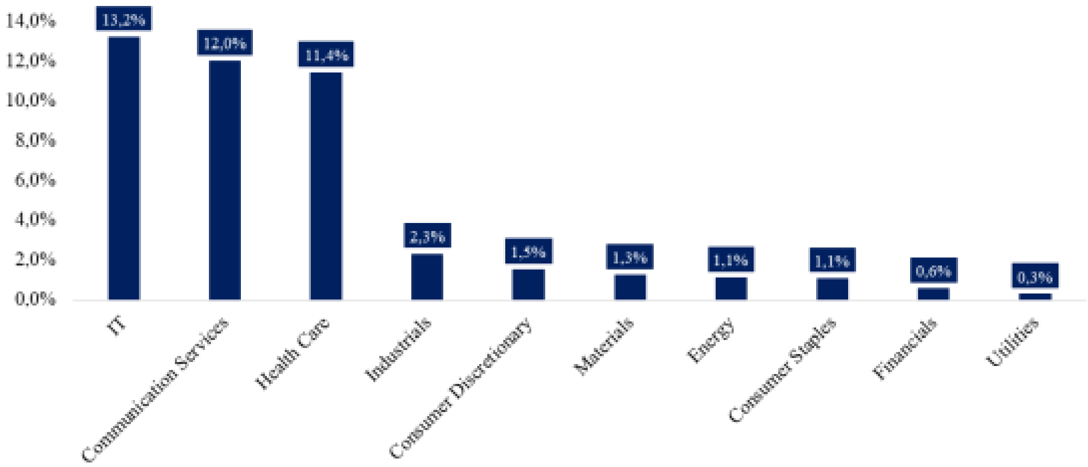
Prispevek te magistrske naloge je v zagotavljanju poglobljenega razumevanja povezave med vlaganji v raziskave in razvoj ter finančno uspešnostjo podjetij, kar lahko služi kot koristna usmeritev za menedžerje, vlagatelje in oblikovalce politik pri razvoju učinkovitih strategij za spodbujanje inovacij in konkurenčnosti na trgu. Poleg tega rezultati prispevajo k razumevanju dejavnikov, ki lahko omejijo ali spodbudijo uspešnost R&D aktivnosti, kar predstavlja temelj za prihodnje raziskave in praktično uporabo.

Appendix 2: R&D expenses 2013 – 2022 per sector *(source: Own work)*

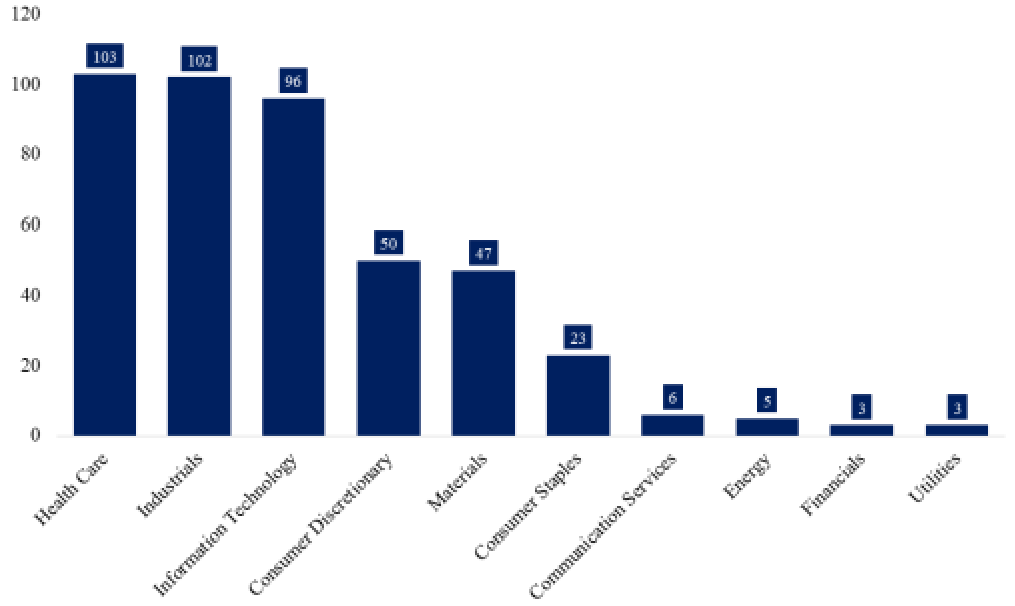


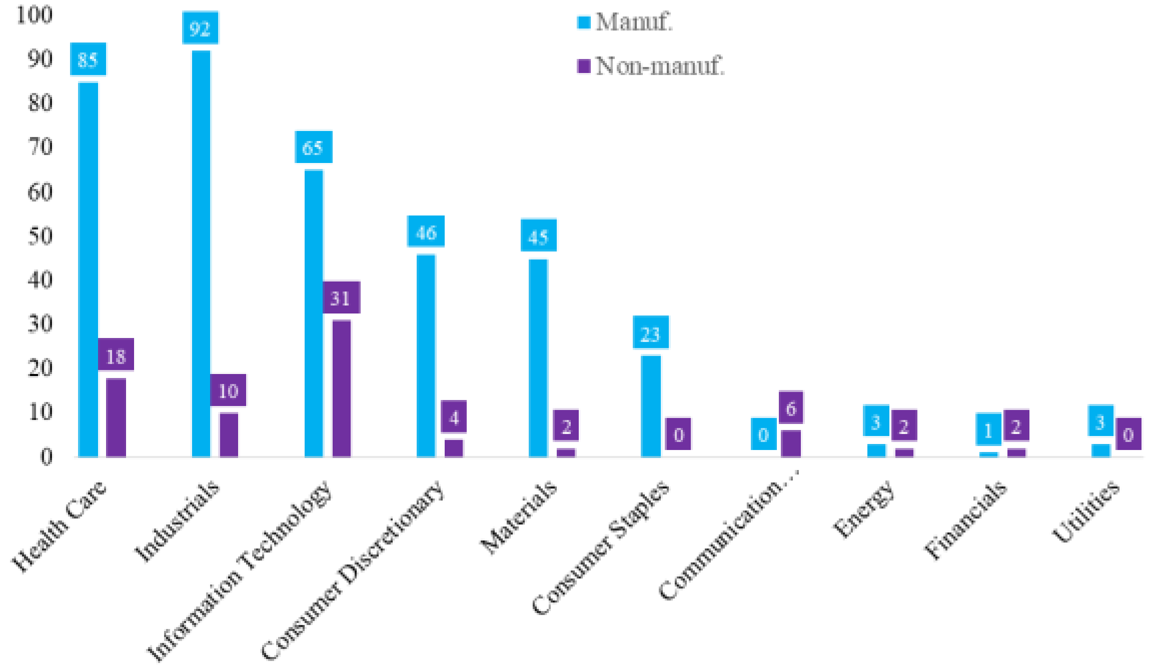
in EUR'm

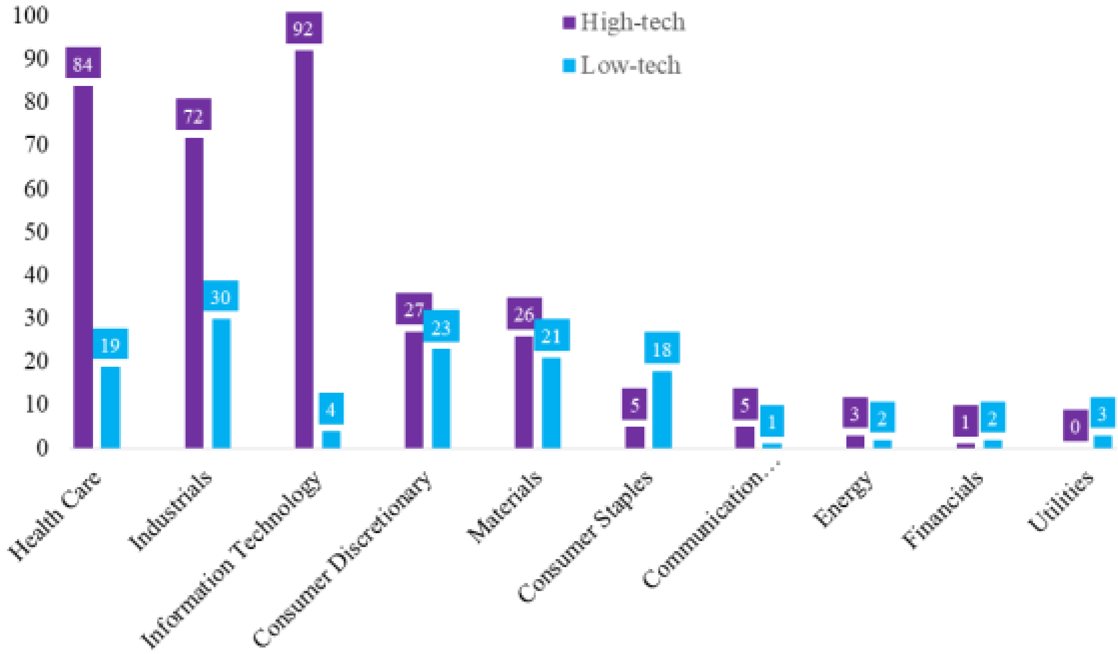
Appendix 3: Average R&D intensity 2013 – 2022 per sector ***(source: Own work)***



Appendix 4: Distribution of companies across sectors *(source: Own work)*







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Health Care
Industrials
Information Technology
Consumer Discretionary
Materials
Consumer Staples
Communication…
Energy
Financials
Utilities