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The impact of R&D investment on firm performance: a comparison of high- and non-high-tech SMEs

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Abstract

This paper investigates whether there is a difference in the impact of R&D investment on firm performance in high-tech and non-high-tech small and medium-sized enterprises (SMEs). I apply the pooled ordinary least squares (OLS) regression method concerning OECD countries with 1502 high-tech firm years and 3501 non-high-tech firm years during the period 2009-2017. My findings show that R&D intensity is negatively associated with firm performance, for both high-tech and non-high-tech SMEs. The impact of R&D intensity on firm performance is greater for high-tech SMEs. I also find that smaller, older and higher leveraged SMEs restrict firm performance more quickly than bigger, younger and less leveraged SMEs, for both high-tech and non-high-tech SMEs. However, firm age has a greater impact in non-high-tech SMEs and firm size has a greater impact in high-tech SMEs.

Table of contents

1. Introduction ... 1
2. Literature review and hypothesis development ... 3
   2.1 Literature review ... 3
      2.1.1 Introduction to R&D investment ... 3
      2.1.2 Theories on the role of R&D ... 5
         2.1.2.1 Resource-based theory ... 5
         2.1.2.2 Knowledge-based theory ... 7
         2.1.2.3 Transaction cost theory ... 8
         2.1.2.4 Organizational learning theory ... 10
      2.1.3 Empirical evidence ... 11
         2.1.3.1 Impact of R&D on firm performance ... 11
         2.1.3.2 Impact of R&D on industry differences ... 16
         2.1.3.3 Impact of R&D on other firm factors ... 18
         2.1.3.4 Impact of R&D on innovation ... 19
   2.2 Hypothesis development ... 21
3. Methodology ... 24
   3.1 Research Methods ... 24
      3.1.2 Ordinary Least Squares (OLS) ... 24
      3.1.3 Fixed/Random effects ... 26
      3.1.4 Generalized Method of Moments (GMM) ... 28
      3.1.5 Quantile regression ... 29
      3.1.6 Non-linear regression ... 30
      3.1.7 Equations ... 31
   3.2 Model used in this study to test the hypothesis ... 32
   3.3 Variables ... 34
      3.3.1 Dependent variables ... 34
      3.3.2 Independent variables ... 35
      3.3.3 Control variables ... 37
   4. Data ... 40
4. Results ... 42
   4.1 Descriptive statistics ... 42
   4.2 Portfolio Analysis ... 45
   4.3 Univariate analysis ... 47
   4.4 Regression results ... 48
      4.4.1 Full sample results ... 48
         4.4.1.1 Correlation tables ... 48

4.4.1.2 OLS results ... 49
4.4.2 Split sample results ... 51
4.4.2.1 High-tech correlation tables ... 51
4.4.2.2 High-tech results ... 52
4.4.2.3 Non-high-tech correlation tables ... 53
4.4.2.4 Non-high-tech results ... 53
4.4.3 Robustness results: Outcomes with R&D intensity 2 ... 56
4.4.3.1 High-tech correlation tables ... 56
4.4.3.2 High-tech results ... 56
4.4.3.3 Non-high-tech correlation tables ... 57
4.4.3.4 Non-high-tech results ... 58
4.4.4 Robustness results: Outcomes with lag in the dependent variables ... 59
4.4.4.1 High-tech correlation tables ... 59
4.4.4.2 High-tech results ... 60
4.4.4.3 Non-high-tech correlation tables ... 61
4.4.4.4 Non-high-tech results ... 61
4.4.4 Quantile regression outcomes ... 63
4.4.4.1 High-tech results ... 63
4.4.4.2 Non-high-tech results ... 64
5. Conclusion and discussion ... 66
Appendix 1: Differences across prior studies ... 68
Appendix 2: Aggregate R&D intensity on industry level ... 73
Appendix 3: Outcomes full sample ... 74
Appendix 4: Outcomes split samples ... 75
Appendix 5: Robustness outcomes with R&D intensity 2 ... 77
Appendix 6: Robustness outcomes with 2-year lag ... 79
Appendix 7: Quantile regressions ... 81
References

1. Introduction

Technology is penetrating in today's highly competitive environment. Management constantly seeks to improve the capabilities of their firm to gain competitive advantage to stay ahead of competition. Innovations causes for enormous changes in the way companies are managed and subsequently influences firm performance and value creation. Innovative activities are recognized as one of principal essential tasks to stay competitive and profitable (Vithessonthi & Racela, 2016). As data availability, statistical techniques and computing power have improved over the last decades, researchers in the field of strategic management have shown increasing interest in explaining performance differences among firms (Hawawini, Subramanian, & Verdin, 2003). Additionally, the European Commission (2015) has concluded that small and medium-sized enterprises (SMEs) are considered as the fundamental drivers of economic and employment growth in developed countries.

Despite the unpredictability of future performance and estimation difficulties related with research & development (R&D) investments, empirical studies on the impact of R&D investment on firm performance have increased over time. The SME literature shows that R&D investment is a crucial driver of firm performance. Investing in R&D gives firms the ability to develop new and existing products, services and advance in more efficient productive processes. The empirical evidence of the impact of R&D intensity on firm performance generally describes a positive impact.

Besides the fact that R&D investment gives firms the ability to develop new and existing products, services and processes, it is also particularly important, as R&D investment stimulates strategic cooperation among firms and increases the absorptive capability of a firm (De Jong & Freel, 2008). This denotes that the knowledge created from the relationship formed with external agents increases, when firms invest more in R&D. Moreover, Rogers (2004) stated that R&D investment contributes to higher diversification and subsequently higher competitive power. SMEs that invest substantial amounts in R&D are more likely to compete innovatively. R&D activities are associated with higher export performance. Investing in R&D empowers firms to increase their export performance, which subsequently contributes to making the firm more competitive (Lefebvre, Lefebvre & Bourgault, 1998). However, R&D investment causes for the creation of intangible assets and subsequently leads to a higher level of risk. An increase in risk could cause for restrictions in obtaining external financing, following difficulties in increasing firm performance.

The majority of the studies concerning the relationship between R&D and firm performance have not made a distinction between high-tech and non-high-tech SMEs. High-tech SMEs are considered as important for economic and employment growth, especially in European countries as high-tech SMEs activities are crucial to attain structural transformation of economies (European Commission, 2015). Technological opportunities vary across industries and subsequently industrial environment may moderate the impact of R&D investment on firm performance. Therefore, the impact of R&D on firm performance may differ for high-tech SMEs in comparison with non-high-tech SMEs. Not making this distinction in the sample could lead to biased results. The literature generally describes a positive impact of R&D on firm performance, independently of taking into account of the industry in which a firm operates. Nevertheless, according to the literature, conflicting evidence is found between high-tech and non-high-tech firms regarding this relationship.

By making the distinction between high-tech and non-high-tech SMEs when investigating the impact of R&D on firm performance, this study extends prior literature in explaining whether high-tech SMEs experience superior performance. Therefore, the following research question will be answered in this thesis: Do high tech SMEs experience superior performance in comparison with non-high-tech SMEs? To do so I use two samples, high-tech SMEs and non-high-tech SMEs. Data is gathered from the ORBIS database over the period 2009-2017. The full sample consists of 5003 firm years, with 1502 high-tech firm years and 3501 non-high-tech firm years. OLS regression with a pooled dataset is done to test the hypothesis. Besides the original results with no lag in the dependent variables, the OLS regression is repeated with a 2-year time lag in the dependent variables and a different measure of R&D investment as robustness checks. Furthermore, the results of quantile regressions will be compared with the results of the pooled OLS outcomes.

The remainder of this paper is structured as follows: in chapter 2 the literature view on theories and empirical evidence and the hypothesis development are presented. Chapter 3 describes various research methods, the model used to test the hypothesis and the data used in this study. Chapter 4 reports the univariate and regression results. Lastly, in chapter 5 the conclusion and discussion are presented.

2. Literature review and hypothesis development

2.1 Literature review

2.1.1 Introduction to R&D investment

Successful innovative activities undertaken by companies benefits consumers by offering a greater or better choice of products and services. Besides consumers benefits, it enables firms to gain higher firm performance, by performing new product development and managing production processes more efficiently. Corporate innovative activities are accomplished by investing the firm's resources in Research & Development (R&D). R&D investment is a driving force for experiencing better firm performance as it helps to develop the companies' capabilities, amplify its capacity to absorb new technologies and to match technological possibilities, which sustain its position in the market (Prahmod et al., 2012).

R&D investment refers to innovative activities undertaking by firms to identify new facts and ideas and develop the ideas into tangible products and services. Besides the development of new products and services, companies also undertake R&D in order to develop new procedures, which helps to the growth and enlargement of their operational activities. There are two principal R&D forms that have emerged considering the difference in R&D investment across industries. Firstly, the experimental and theoretical work undertaken, often tasked to develop new products, is commonly referred to as basic R&D (Organisation for Economic Co-operation and Development, 2015). Secondly, the other form of R&D is done with applied research in scientific, technical or industrial fields, which is aimed to facilitate the development of future products or to improve existing products. This method is referred to as applied R&D (Bertrand, 2009). Basic R&D initiates companies to acquire new knowledge often without having any specific goal, whereas applied R&D is a systematic study to determine and develop products, services or processes and is performed with a more specific goal in mind (Organisation for Economic Co-operation and Development, 2015). Henard and McFayden (2005) suggest that basic and applied R&D are complementary, as basic R&D develops the stock of knowledge from which applied R&D projects are drown. Moreover, R&D may be performed in an internal department of a company, however it can also be outsourced to specialists or universities for instance. Outsourcing R&D is appealing to small business, since the lack of expertise and manpower is greater for these kind of corporations. A combination is also possible and is most common in multinational companies. R&D takes places in companies of all sizes, however bigger companies experience greater possibilities when investing in R&D.

Corporate R&D investment was first done by Thomas Edison, who created so called 'research and development laboratories', which drastically transformed the process of technological research. Edison created a different style and approach by adding the concept of R&D management, he empowered a robust method of invention by systematically saddling the talent of individuals. More specifically, Edison focused more on being a research director, instead of being a tinkerer. In his laboratories he started supervising a team of chemists and engineers and used informal management techniques to accomplish highly specified goals (Carlson, 1988). After Edison's practices became generally known, companies saw that an organized approach to research may contribute to having a higher competitive advantage. In the early 1900s, management realized that this new approach could not only lead to the invention of new product and services, but could also create entire new industries.

R&D investment reflect the firm's strategic choices and commitments to develop firm-specific capabilities and routines. R&D is focused at creating competitive advantage and increasing firm performance (Vithessonthi & Racela, 2016). The creation of new products and services may be a crucial factor in the survival of a company. Due to heavy competition and changing customer needs and the rapid changing environments, corporations must perpetually stay competitive. Besides companies that benefit from investing in R&D, the whole economy of a nation benefits as well. Robert Solow received a Nobel Prize for his research on economic growth and concluded that the gross national product of a nation increases more due to technological investment than to just capital investment (Solow, 1994).

However, managing corporate R&D investment brings along complications. Investing in R&D does not necessarily guarantee in experiencing higher firm performance. Researchers do not know in advance what the outcome of certain R&D investment and activities. Therefore, investing in R&D causes for uncertainty, since both the development and the realization of R&D investment carries unpredictability among its profitability. Moreover, measuring R&D performance is another complication. Measuring the contribution and performance of R&D investment has become critical due to the increasingly nature of the costs and risk of R&D (Lazzarotti, Manzini & Mari, 2011). The last decades, researches have tried to search for appropriate frameworks to measure the performance created by investing in R&D. However, there exists no general accepted framework to measure R&D performance, since it is too complex a subject to cover all needs. In addition, researchers have to an increasingly extend investigated the impact of R&D on various kinds of firm performance measures. Lastly, the literature reveals that there exists a general consensus that R&D investment has a positive impact on firm performance.

R&D investment is commonly not performed to accomplish a higher firm performance immediately. Rather, investing in R&D is primary focused on the goal of long-term profitability. In addition, R&D is most often done in industrial, technological and pharmaceutical industries. For instance, high-tech companies invest in R&D to remain innovative and create competitive advantage, due to the nature of the high-tech industry environment, which changes continuously.

2.1.2 Theories on the role of R&D

2.1.2.1 Resource-based theory

The resource-based theory is used in various studies investigating the impact of R&D on firm performance. The resource-based theory, also referred to as the resource-based-view, is a managerial framework used to explain the competitive advantage of firms based on the possession of their tangible and intangible resources. The works by Penrose (1959) and Barney (1991) are generally commended as the initial and essential works in the publication of the resource-based theory. The resource-based theory explains differences in firm profitability that are caused by firm-specific factors (Barney, 1991). This theory provides management a strategic method in evaluating potential components that can be utilized to develop competitive advantage. The resource-based view offers the means of evaluating potential firm-specific factors that can be deployed to achieve competitive advantage. There are two types of resources, which are tangible and intangible. Tangible resources are physical resources, such as buildings, machinery and capital, which can be obtained by simply buying them with the firm's funds. Intangible resources are resources that have no physical presence, such as brand reputation and goodwill, which are created by the firm itself.

Barney (2001) describes firm resources as: "all assets, capabilities, organizational processes, firm attributes information, knowledge etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness". Furthermore, Peteraf (1993) stated that the resource-based theory explains differences in firm profitability, which are not associated with industrial differences. Firms success is therefore not entirely dependent upon the industry structure, rather the function of resources and capabilities controlled by the firm, deployed by managers and developed and extended by the organization (Schendel, 1994). In addition, the resources and capabilities are the primary constants upon which a firm establishes its identity and frames its strategy. They are the fundamental sources of the firm's profitability (Grant, 1999). It can be argued that a firm's resources are considered as heterogeneous. This heterogeneity in resources is needed to gain competitive advantage. However, not all resources are of the equivalent potential and importance to arise into a source of sustainable competitive advantage (Fahy & Smithee, 1999). Maintaining sustainability of competitive advantage depends on the extent to which resources can be copied or substituted. Employing the resource-based view, strategic management seek to adopt the foremost strategy and competitive position to utilize the firm's resources and capabilities. Nevertheless, Barney (2001) has pointed out that making practice of the relationship between resources of competitive advantage and employing successful strategies can cause for complications. Therefore, strategic management will have to invest in organizational learning to develop and maintain crucial resources and capabilities in their firm. Lastly, researchers have focused on the importance of intangible resources, for instance R&D investment. However observing, quantifying and measuring these sort of capabilities cause for complications, making the study of such organizational capabilities difficult (Deeds, 2001). The following sections describe how various researchers have exploited the resource-based theory to test the impact of R&D on firm performance.

Booltink and Saka-Helmhout (2018), Lome, Heggeseth and Moen (2016), Andras and Srinivasan (2003), Ehie and Olibe (2010), Wang (2009) and Ho et al. (2005) have exploited the resource-based theory on their research of the impact of R&D investment on firm performance. The authors that investigate a positive impact of R&D investment on firm performance described that one of the key determinants of firm performance is the capacity to assemble and apply the proper type of resources, which may lead to the development of new products with particular customers benefits in an environment of technological change and subsequently increases the competitive advantage of the firm. R&D investment may be seen as an addition to the firm's stock of knowledge, as this resource is important for the development of knowledge capabilities and the creation of innovations. Firms develop their strategy by focusing on its resources as of pivotal importance. The capability of firms lies in the capacity to perform an activity by organizing and coordinating the productive services of a group of resources. Given resources constraints, firms will have to prioritize their investments to reach maximum performance, based on their core competences. Organizations therefore need to allot their assets efficiently in order to adapt and survive in competitive environment. the resource-based view paradigm considers investment in valuable resources, especially R&D and innovative investments, as competing for a firm's critical resources. Additionally, R&D stimulates innovation and enhances technology transfer by a firm's absorptive capacity, which is the capability to identify, absorb and exploit outside knowledge. R&D investment is intangible by nature and difficult to replicate by other firms. Therefore, intangible assets are more likely to accomplish the necessary requirements for sustaining a sustainable competitive advantage. Building on the resource-based view, firms that invest in R&D are likely to experience superior firm performance, due to the fact that R&D activities lead to the development of resources which are valuable, rare, inimitable and non-substitutable resources empowers organizations to preserve competitive advantage.

However, drawing on the resource-based theory, Booltink and Saka-Helmhout (2018) argued, in their research on the impact of R&D on non-high tech SMEs performance, that investing in R&D may be subject to time compression diseconomies or exhibit decreasing returns. Which implies that the higher R&D stock of knowledge, the more likely it is to accumulate R&D marginal know-how. Competitive advantage arises from technological and organization capabilities. competitive advantage and firm performance results are a consequence of firm-specific resources and capabilities. Subsequently Booltink and Saka-Helmhout (2018) describe that non-high-tech SMEs search for interdependent assets to enhance knowledge capabilities and to improve innovation performance and growth. However, time and resource restrictions in developing these capabilities internally would enlarge a firm's need to cooperate in accessing interdependent technologies and a broader scope of assets. Collaboration among firms may allow small firms to complement their resource endowments and subsequently help these firms to overcome small-size related burdens. Nevertheless, not all collaborations will make an equivalent contribution to developing capacities, which means that firms may not be able to select and manage collaborations effectively. Cooperation with other firms require time, energy and attention to establish and maintain and subsequently involve costs. As the amount of collaborations grow, inherent complications in human capital and acquisition of resources will grow as well. Subsequently, the efforts affiliated with establishing and maintaining collaborations may result in decreasing or even negative returns to capacity development.

2.1.2.2 Knowledge-based theory

The knowledge-based theory of the firm, also called knowledge-based view, regards knowledge as the most important resource of a firm. Similar to the resource-based theory, the knowledge-based view considers that knowledge-based resources are generally difficult to imitate. This theory considers organizations as heterogenous entities loaded with knowledge. Distinctive characteristics of knowledge resources are crucial in a firm as they may ensure sustainable competitive advantage. Furthermore, the knowledge-based theory also demonstrates the important role of intangible resources in a firm, as they may have a positive impact on the competitive position of the firm. These resources are referred to the as the principal resources that generate sustained competitive advantage. There exist great similarities with the resource-based view, therefore the knowledge-based view is referred to as an extension of the resource-based theory of the firm (Rouse & Daellenbach, 2002; Grant, 2002).

Attributable to a shift of material-based production to information-based production in the last decades, there has been a significantly higher focus on knowledge resources (Child & McGrath, 2001). In contrast to the resource-based view, the knowledge-based theory describes knowledge-based capabilities as the most strategically important factors to create and sustain competitive advantage. One of the key factors to sustain competitive advantage in high performance firms is the ability to learn faster than competitors. This is based upon the creation of barriers to imitability and making it difficult for competitors to recreate the evolution that a firm develops, which establishes the grounds for competitive advantage (Lei, Hitt & Bettis, 1996). Rugman and Verbeke (2002) describes that capabilities in a firm lead to superior performance, when they are difficult to imitate, valuable to customers and non-substitutable. Building upon the difficulty to imitate knowledge-based resources, the specific and complex knowledge that is developed internally, will generate long-term benefits in a firm (McEvily & Chakravarthy, 2002). According to Zack (2003), the knowledge-based view may lead to sustainable competitive advantage based on having more and better knowledge about certain aspects than competitors, alongside the time complications of competitors to obtain similar knowledge. Moreover, knowledge is embedded and carried through various entities of the firm, such as a firm's system, employees, routines and culture. For instance, the approach to the organization culture of a firm is consistent with the perspective of the knowledge-based theory. Organizations may learn through activities that involve cultural artefacts, subsequently organizational learning allows firms to acquire and preserve its knowledge capabilities (Balogun & Jenkins, 2003). The following section describes how this theory is exploited in the research on the impact of R&D investment on firm performance.

According to Sullivan (2000) and Teece (2006), the knowledge-based view differs from the-resource based view, since the focus of the knowledge-based theory is based on the creation and development of the firm's knowledge. Creating value in a firm is primarily the role of intellectual capital, whereas the resource-based theory is focused on the creation of profits from the combination of intellectual capital and tangible resources. The resource-based perspective focuses entirely on strategies for exploiting firm-specific assets. therefore, the core focus of the knowledge-based theory is on value creation, while for the resource-based theory it is value extraction. Another difference is that people are considered as human capital in the knowledge-based view, although the focus of the management with a resource-based view is on the structural capital of the firm (Sullivan, 2000).

The knowledge-based theory is employed by Vithessonthi and Racela (2016) as theoretical framework to test the short- and long-run effect of R&D intensity on firm performance. Using the work of Grant (1996), these authors describe that the knowledge-based states that knowledge is a heterogeneous and unique resource, which makes this resource difficult to imitate by competitors. This theory is integrated with the innovation and international strategy literature to test their hypotheses. Furthermore, R&D investment are among the most commonly used proxies for innovation and therefore they regard R&D investment as mechanism for the fundament of a firm's knowledge base and innovative capabilities. Similar to the knowledge-based theory, R&D investments are aimed to create sustainable competitive advantage and increase firm value. Moreover, it reflects a firm's strategic choice and commitment to develop firm-specific capabilities and routines to boost research and discoveries, which subsequently assist the development of technical knowledge that can be utilized with current technologies, organizational processes and products and services of a firm. Vithessonthi and Racela (2016) build upon this theory to empirically test whether mixed results in the literature on the impact of R&D on firm performance is conditional on the measurement of firm performance and firm-level characteristics.

2.1.2.3 Transaction cost theory

The transaction cost theory, also called the transaction cost reasoning or the transaction cost approach, refers to the cost of providing goods or services through the market. North and North (1992) described that institutions are the fundament of the determination of transaction costs. Subsequently, institutions that have low transaction costs, improve their economic performance. The publication by Williamson (1981) is considered as the pivotal work on the transaction cost theory. According to Williamson, analysis of transaction costs is an approach to the study of organizations that joins economics, organization theory and aspects of contract law and provides a consolidated understanding for various sets of organizational phenomena. The transaction theory regards transactions as the basic unit of analysis, with frequency, specificity, uncertainty, limited rationality and opportunistic behavior being the key determinants of transaction costs (Williamson, 1981). One of the key dimensions of the transaction cost theory refers to human agents who are subject to bounded rationality. Bounded rationality of individuals is considered as limited, based on the limited competences and information of these individuals. Williamson describes that all economic exchange may efficiently be organized by contract. However, the complexity of contractually relevant aspects makes the grasping of bounded rationality difficult. According to Williamson, critical dimensions for transactions are uncertainty, frequency and degree of durability and are considered as the cause that incomplete contracting is the best that can be achieved.

The transaction cost theory is used by Wang (2009) and David, O'Brien and Yoshikawa (2008) to test the impact of R&D on firm performance in high-tech industries. More specifically, Wang (2009) used the concept of bounded rationality to test whether there exists a negative impact of R&D on firm performance. Firstly, empirical literature on the impact of R&D on firm performance have accepted a positive relationship. However, there exists empirical evidence that does not fully demonstrate that positive relationship. Using the work of Williamson (1981), he describes that under the transaction cost theory and the bounded rationality assumption, firm will invest internally R&D rather than out-sourcing R&D investment. The reasoning behind this argument is that technological innovation and market expansion are subject to opportunistic behavior of the concerning parties. R&D investment involves a high degree of uncertainty considering the nature and timing of the output. Which means that investing in R&D does not necessarily result in greater output. More specifically, customer demand may fluctuate and R&D investment cannot be recouped. Therefore, R&D investment often requires transaction specific investments in intangible assets that are difficult to imitate. David et al. (2008) add that debt and equity are governance structures for the safeguarding of the capital that has been invested in a firm. Utilizing the transaction cost theory, they explore the attributes of investment that pose the hazards associated with R&D investment and firm performance. Additionally, the combination of high demand uncertainty and large R&D investment costs could subsequently cause that investing in R&D might not lead to the desired performance. Lastly, R&D investment accompanied by risks are expected to have a negative effect on firm performance, as the firm faces a higher chance of financial distress. Innovation process of a firm is filled with high risk and high uncertainty, therefore the risk should be of a negative value expect for the success of R&D investment. Lastly, Robertson and Gatignon (1998) utilized the transaction cost theory to investigate technology alliances, which seeks to leverage resources and competences to develop sustainable innovations, with a primarily focus on R&D investment. The authors explain that their conceptualization proposes three relevant constructs to technology development decision processes, which are: asset specify, external uncertainty and behavioral uncertainty. Transactions differ across these three critical constructs and align with governance structures. Firstly, transaction specific assets involve investment in physic and human capital and if these assets were to be reduced, this would cause for losing productivity value. External uncertainty is described as demand uncertainty, which is concerned with the fluctuation of demand and unpredictability of the demand and technological uncertainty, which refers to the possibility of improvement in technology. Lastly, behavioral uncertainty is referring to the difficult in the observation and measurement of transacting parties to contractual arrangements.

2.1.2.4 Organizational learning theory

The organizational learning theory refers to creating, maintaining and shifting knowledge within a firm. According to the organizational learning theory, an organization improves over time, due to the experience it gains. The experience that is gained allows organizations to gain competitive advantage. From an organizational development perspective, the work by Argyris and Schon (1978) Is often referred to as the pivotal work of the organizational learning theory. According to them, organizational learning is a product of the organizational inquiry, which denotes that if the expected outcome differs from the actual outcome, agents in the organization will try to understand and solve this variability in outcomes. The individuals of the organization will interact with each other and organizational learning will take place. Organizational learning is a complex mechanism, which relies on the interpretations of past events. Argyris and Schon (1978) conclude that learning is a direct product of this interaction between individuals in a firm.

Argyris and Schon (1978) created two models of how individuals may generate organizational learning in an organization, namely the espoused theory and the theory in use. The espoused theory refers to the formal organization. Every firm has a set of rules regarding the way employees should conduct in order to execute their jobs. Instructions in an organization are specific and narrow the focus, which subsequently confines individuals to take a certain path to solve problems. Moreover, the theory in use refers to the way how things are actually accomplished in an organization. This theory proposes that individuals rarely follow the espoused theory model and rely on their own understanding of solving problems, through for instance interaction. The theory in use describes that problems are solved according to the social way that employees solve problems and learn.

There are three types of learning in an organization, which are single-loop learning, double-loop learning and deuteron learning (Argyris & Schon, 1978). Firstly, single-loop learning refers to the process wherein mistakes are corrected by using a different strategy or method that is expected to solve a different, but successful outcome. Single-loop learning happens when organizations detects a mistake and corrects for it using present policies and routines. Secondly, double-loop learning refers to correcting mistakes by reevaluating the initial goal. Therefore, it can be stated that the theory in use method is changed to correct the created mistakes. More specifically, strategies and assumptions may be changed to create a more efficient way to solve a certain problem. Second-loop learning occurs when organizations detect a mistake and changes its policies and routines, before taking actions to solve a certain mistake. Lastly, deuteron learning refers to improving the learning system itself. This type of learning refers to the behavioral components that determine how learning takes place. Therefore, this type of learning is also called ‘learning how to learn’.

This theory is used by Lin (2003) and Wang (2009) who test the impact of R&D on firm performance. Wang (2009) test for a specific threshold perspective that takes a particular interoperation of the organizational learning theory. There exists evidence supporting that organizational learning is a critical driving force for organizations who intends to enhance the marketing of a new product or technology (Argyris & Schon, 1978). Citing the work by Mavondo, Chimhanzi and Steward (2005), Wang (2009) describes that organizational learning refers to the process by which a firm acquires information, knowledge, understanding and know-how that lead to changes in the firm’s routines. Furthermore, R&D activity is a key source of organizational learning (Mowery, 1981). Lastly, innovative activities may have difficulties making a technological breakthrough. Therefore, firm performance may be weakened with increased investment in R&D up to a certain level, beyond this level the firm will experience greater firm performance. Lastly, Lin (2003) describes that the organizational learning perspective sheds light on technological learning processes and proposes a conceptual model with three dimensions, which are causal ambiguity, firm specificity and organization intelligence. These three dimensions are used to explain technological learning performance on which their research is based. Utilizing the organizational learning theory, the researcher gives an answer to why and how firms with limited R&D investment resources can gain competitive advantages through the transfer of technology.

2.1.3 Empirical evidence

2.1.3.1 Impact of R&D on firm performance

Considering the literature on the relationship between R&D and firm performance, there are various performance measures to assess firm performance, taken into account its relationship with R&D. There is evidence that R&D is positively related with various types of market-, operating- and accounting-based performance measures. (Guo, Wang & Wei, 2018; Booltink & Saka-Helmhout, 2018; Gui-long, Yi, Kai-gua & Jiang, 2017; Vithessonthi & Racela, 2016; Aggelopoulos, Eriotis, Georgopoulos & Tsamis, 2016; Lome, Heggeseth & Moen, 2016; Pramod, Krishnan and Puja, 2012; Ehie & Olibe, 2010; Falk, 2010; Yeh, Chua, Sher & Chiu, 2010; Wang, 2009; Anagnostopoulou &Levis, 2008; Lin, Lee & Hung, 2006; Ho, Keh & Ong, 2005; Bae & Kim, 2003; Andras & Srinivasan, 2003; Deeds, 2001).

Gui-long et al. (2017), Aggelopoulos et al. (2016), Andras and Srinivassan (2003) and Guo et al. (2018) have found a positive impact of R&D on various operating- and accounting-based performance measures. Gui-long et al. (2017) investigated the impact of R&D intensity on firm performance in an emerging market, more specifically china's electronics manufacturing firms. Using pooled Ordinary Least Squares (OLS) linear regressions they find that R&D intensity positively affects the ratio of the value of a firm's profitability relative to its total sales. The results show the effectiveness of china's R&D investment in emerging industries' innovation and economic achievements in the recent years. In addition, they subsequently used a quantile regression to confirm the initial findings. The quantile regression findings are consistent with the outcomes of the pooled OLS regressions. The evidence of the quantile regression method suggests that R&D intensity makes a more important contribution when firm's with better performance are considered. The findings of this in-depth regression method show that firms with higher R&D intensity are subject to having a better accounting performance. R&D intensity makes an important contribution to the superior performance of the better-performance quantile firms. Lastly, the contribution of this study is that it employs various regressions methods to test the impact of R&D on firm performance, which present more robust statistical results in contrast to most literature considering this relationship. Furthermore, Andras and Srinivasan (2003) also test whether R&D intensity has an impact on the profit margin of a firm. The results of their study are consistent with Gui-long et al. (2017), since the findings reveal a positive impact of R&D intensity on the profit margin of a firm. However, this research is limited, due to the lack of control variables and a poorly described data chapter, which does not specify which countries data is gathered from. It also compares consumer product organizations with manufacturing product organizations. However, in their sample, manufacturing product organizations are significantly more represented than consumer product organizations. Considering their full sample of consumer product organizations, R&D intensity is gathered from mere 46 companies, which is more than 10 times lower than manufacturing product organizations. Therefore, the consumer product organizations are underrepresented in this study. Lastly, whereas the vast majority of the studies in the literature use a period over multiple years, this study uses data from mere one year and therefore have to deal with a low sample, which may cause for bias in the findings. Moreover, Aggelopoulos et al. (2016) tested the impact of R&D intensity on operation performance in a small open economy. Utilizing a longitudinal dataset concerning Greeks SMEs, the results of this article confirm previous results, as they highlight a positive role of R&D intensity in the improvement of the operational cash flow and gross profit margin of a firm. The influence on the performance of R&D intensity was positive for all firms, regardless of the industry in which they were operating. Lastly, Guo et al. (2018)

investigated the effect of R&D on firm performance for Chinese listed manufacturing firms, conditional on their strategic positions. This study has a clear data chapter, which describes how the data is gathered and the sample distribution, which is mostly even distributed over the sample period. The findings show a positive impact of R&D on operating- and accounting-based firm performance measures for firms that pursue a product differentiation strategy. For firms pursuing a cost leadership strategy, an inversed U-shaped relationship between R&D and firm performance is found for non-state-owned firms. Lastly, the authors of this paper state that findings provide valuable outcomes for managers on the efficient allocation of R&D resources in china.

In addition, Falk (2012) and Lome et al. (2016) have found a positive impact of R&D investment on various growth performance measures. Falk (2012) investigates the relationship between R&D intensity and firm growth using a dataset of Austrian firms during the period 1995-2006. Utilizing the least-absolute deviation (LAD) method, he finds that R&D intensity has a positive impact on both employment and revenue growth in the following 2 years. Falk (2012) states that his findings are robust, with respect to different measurements of R&D intensity, different time lags and different time periods. Furthermore, quantile regressions are used as a robustness check and the findings state that the impact R&D intensity is significantly for 0.3 of the highest quantile firms on employment growth. Lastly, he finds that this impact of R&D on employment and sales growth decreases significantly over time. Lome et al. (2016) investigated the effect of R&D on firm performance and specifically test whether R&D-intensive firms handle a financial crisis better. Firm performance is measured by yearly revenue growth and aggregate revenue growth. Utilizing binary logistic regression on a dataset of Norwegian manufacturers, they find that firms who had devoted considerable resourced to R&D investment performed significantly better than other firms, throughout the financial crisis in the late 2000s. This relationship was stronger than the one found during a period of normal growth, which implies that the significance of R&D investment is accentuated during a period of crisis. Therefore, firms with credit constrains should take note of the importance of R&D during turbulent times, before cutting down on these investments. Lastly, by investing in R&D, managers may increase revenues, while at the same time preparing their firm for the next inevitable recession. In contrast to previous findings, Vithessonthi and Racela (2016) investigated the short- and long-run effects of R&D intensity on firm performance. The study's dataset consists of non-financial firms listed on the United States stock exchanges during the period 1990-2013. The short-run performance is measured by operational performance. In contrast to the findings Aggelopoulos et al. (2016), Vithessonthi and Racela, (2016) found that R&D has a negative impact on the operating performance on a firm. However, this negative effect is only evident for high R&D-intensive firms.

Although there exists a general consensus that R&D investment has a positive impact on firm performance, Booltink and Saka-Helmhout (2018), Wang (2009) and Yeh et al. (2010) have found that there exists a certain threshold in the relationship between R&D investment an firm performance. Booltink and Saka-Helmhout (2018) tested the effect of R&D intensity on the performance of non-high-tech SMEs. In contrast to other studies, this study uses both manufacturing and service firms to test this relationship. Using survey data of European firms, they find an inverted U-shaped relationship between R&D intensity and firm performance. Investment in R&D leads to higher performance, up until a critical threshold. After this threshold, firm performance will diminish. The more non-high-tech SMEs increase their R&D investment after this threshold, the less likely they are to increase R&D knowledge that has an increasingly contribution. The acquisition of knowledge, resource investment and collaborations are more likely to progressively become less efficient. Firm strategies on the capitalization of R&D investment is required to gain competitive advantage in non-high-tech SMEs. Lastly, they conclude that R&D intensity may hinder growth due to increased risks and incapacity to small liabilities or constrained endowment of tangible assets. Besides investigating the impact of R&D on different kind of firm performance measures, Booltink and Saka-Helmhout (2018) also test for the moderating role of internationalization on the impact of R&D on firm performance in non-high-tech SMEs and found that fully internationalized SME require a higher level of R&D than marginally internationalized SMEs to have the same firm performance. They concluded that fully internationalized SMEs are more likely to be directly exposed to global market pressures. Moreover, Wang (2009) adds a proposal of a new unified nonlinear relationship that incorporates an optimal and threshold effect. Investigating panel data of high-tech firms, he finds an inverse S-shaped nonlinearity relation between R&D and firm performance. Wang (2009) adds that an optimal level of R&D corresponds with maximum firm performance. However, there also exists a threshold, which means that a minimum level of R&D is required in order to be effective. His contribution to the literature is that the theoretical gap concerning the nonlinearity relation between R&D and firm performance is investigated and his research adds insights on this gap. This study, however, uses a dataset of mere 40 manufacturing high-tech firms from Taiwan, which may be considered as a small sample. In addition, Yeh et al. (2010) also investigated whether there is an optimal R&D intensity at which a firm is able to maximize its performance among publicly traded Taiwan information technology and electronic firms. Using the advanced panel threshold regression model, they found that there is a threshold effect of R&D on firm performance and demonstrated that via an inverted-U correlation it is possible to identify the level beyond which further increase in R&D intensity reduces firm performance. There exists a positive impact when R&D intensity is less than the threshold value, which denotes that R&D enhances firm performance at this level. However, above this threshold value, R&D has a negative impact on firm performance, which means that further R&D investment would reduce firm performance. Therefore, it is concluded that R&D investment should not be treated as an unlimited investment, since there exists a level beyond which increased R&D investment does not yield proportional rewards. Lastly, the contribution that this article makes is that managers can ascertain the optimal R&D investment level by calculating the threshold levels utilizing the models developed in this study.

Vithessonthi and Racela (2016), Guo et al. (2018), Ehie and Olibe (2010), Anagnostopoulou and Levis (2008), Ho et al. (2005), Bae and Kim (2003) and Deeds (2001) have found a positive impact of R&D on various market-based performance. Besides investigating for short-run effects of R&D intensity on firm performance, Vithessonthi and Racela (2016) also investigate long-run performance effects, which is measured by firm value. The researchers find that R&D has a positive impact on firm value. They also investigate the moderating effect of internationalization and the effect of R&D intensity on firm performance and found that R&D is positively associated with the firm value, however this relationship is weakened by internationalization. Guo et al. (2018) also tested the impact of R&D on both accounting- and market-based performance and confirm previous findings, which were already described above. Anagnostopoulou and Levis (2008) investigated the impact of R&D on firm performance and firm performance persistence. Using a large dataset of firms from the United Kingdom over the period 1990-2003, they find that R&D intensity has a positive impact on risk-adjusted excess returns. In addition, they find that R&D intensity improves the persistence in excess stock returns, which means that the highest R&D intensive firms are found to earn higher risk-adjusted excess returns more consistently in comparison with lower R&D intensive firms or firms that do not invest in R&D. Lastly, this market-based performance persistence is interpreted as consistence with at least some form of market mispricing. Ehie and Olibe (2010) investigated the impact of R&D intensity on firm value as well. Their data consist of firms from the United States over an 18 year period. The findings of this study confirm previous findings as they find a positive impact of R&D investment on firm performance for both manufacturing and service firms. Furthermore, they conclude that their study has the following contributions. The empirical analysis employs the largest dataset up to 2010 and this study compares manufacturing industries with service industries, whereas the majority of other studies compare manufacturing firms with non-manufacturing firms. Moreover, Ho et al. (2005) investigated the effect of R&D on firm value and examine the differences between manufacturing and non-manufacturing United States firms over a period of 40 years. They find that R&D intensity has a positive impact to one-year stock market performances of manufacturing firms but non for non-manufacturing firms. Based on the resource-based view, they state that firms should choose the right resource to optimally enhance its performance. This explains why more than 60% of non-manufacturing firms do not invest in R&D. Lastly, firms should specialize in the resources in which they have competitive advantage or core competence. Bae and Kim (2003) tested the effect of R&D investment on market value of a firms in the United States, Germany and Japan during the period 1996,1998. The findings of this study show that R&D investment has a positive impact on the market value of firms in all three nations. Therefore, capital markets in these nations should value long-term R&D investment particularly. Lastly, for all the three nations, firms with higher stock return volatility are more likely to invest more on R&D. Lastly, Deeds (2001) investigated the role of R&D intensity in creating entrepreneurial wealth in high-tech start-ups. The entrepreneurial wealth created by a firm is measured by market-value-added. The results of this study provide strong evidence that high-tech firms create entrepreneurial wealth by investing resources in R&D investment. The outcomes of this study support the need for continuous involvement of public research institutions and government funding in early stages of development activities. However, the method section is poorly described as a linear regression model is used, but the model used is not specified. Pramod et al. (2012) investigated the impact of R&D intensity on the market valuation of the firm as well. The data used in this study concerns Indian manufacturing firms for the period 2001-2010. They find an inverted U-shaped relationship between R&D intensity and firm value. This indicates a positive impact of R&D on firm value in the beginning, however after R&D investment exceeds a certain optimal level, increasing R&D investment will lower the value of a firm. Lastly, they conclude that managers should treat R&D investment as assets to a firm, as long as the investment is moderate. Therefore, managers should utilize an optimal level of their R&D investment to establish an intellectual capital investment strategy. Whereas multiple studies have found a positive impact of R&D on market-based performance measures, using data of technologic public firms from the United States, Lin et al. (2006) however found that relationship between R&D intensity and the market value of a firm is insignificant. Besides investigating the effect of R&D on firm performance, Lin et al. (2006) investigated the effect of the interaction of R&D and commercialization orientation on financial performance as well. They found that a firm's R&D intensity and commercialization orientation complement each other.

2.1.3.2 Impact of R&D on industry differences

Although there exists a generally accepted consensus on the positive impact of R&D on firm performance, there are various studies concerning the variety across industries on this impact. The following motivations are given in the literature to distinguish between high-tech and non-high-tech firms. High-tech SMEs are considered as important for economic and employment growth, especially in European countries as high-tech SMEs activities are crucial to attain structural transformation of economies (European Commission, 2015). Therefore, Nunes et al. (2012) have used this motivation to ascertain if the relationship between R&D intensity and firm performance is different between high-tech SMEs and non-high-tech SMEs. Moreover, Aggelopoulos et al. (2016) have used findings of the studies done by Tasng et al. (2008) and Chan et al. (2003) to motivate the distinction between high-tech and low-tech industries. These researchers have concluded that technological opportunities vary across industries and subsequently industrial environment may moderate the impact of R&D investment on firm performance. Ortega-Argilés, Piva and Vivarelli (2011), Kumbhakar, Ortega-Argilés, Potters, Vivarelli and Voigt (2011), Ortega-Argilés, Piva, Potters and Vivarelli (2009) and Verspagen (1995) have used the reasoning that the impact of R&D on firm performance may differ across industries, due to difference in investing opportunities as well. These authors stated that technological opportunities and appropriability conditions are especially different across industries and use this as motivation to investigate for industry differences.

Several researchers have investigated the impact of R&D investment on industry differences. For instance, Anagnostopoulou and Levis (2008) tested the impact of R&D intensity on firm performance proxied by revenue growth and gross income. Using a sample of listed nonfinancial firms over the period of 1990-2003 from the United Kingdom and find that R&D is positively associated with sales growth and gross income. However, they only find this positive impact for firms that need to engage in R&D, due to the industry in which it operates. They conclude that the positive impact of R&D on sales growth and gross income is mere present for R&D-intensive industries. In addition, Nunes et al. (2012) have found a U-shaped, quadratic relationship between R&D intensity and revenue growth, however only for high-tech industries. They stated that R&D intensity is a factor restricting growth for low levels of R&D, but found a positive impact of R&D intensity for high levels of R&D investment. For non-high-tech SMEs they find that R&D intensity restricts the growth of a firm regardless of the level of R&D. Eberhart and Maxwell (2004) have investigated firms that had unexpectedly increased their R&D expenditure over the period 1951-2001. The impact of an economically significant increase of R&D is tested on the operating performance. Their findings show an overall positive impact on abnormal profit margins that is experienced when firms increase R&D expenditure significantly. Nevertheless, high-tech firms appear to have greater boosts in operating performance from R&D increase, since both the economically and statistically significance for these kinds of firms are higher. In addition, Chan et al. (1990) have investigated the impact of R&D expenditures and share value. They find that share-price responses to announcements of increased R&D spending are positive on average. However, share price responses based on R&D announcements are positively related with abnormal returns in high-tech sectors, whereas R&D announcements by low-tech firms are associated with negative abnormal returns. in contrast to these findings that show that high-tech firms benefit more from R&D investment, Aggelopoulos et al. (2016) have tested the difference in the impact of R&D on firm performance between high-tech and low-tech firms as well. However, using four different operating-based performance measures, they find no support for this hypothesis. Lastly, a critical note on this comparison is that they merely use 30 low-tech SMEs vs 78-high tech SMEs, which could be considered as low amount of firms, especially low-tech SMEs.

Moreover, Ortega-Argilés et al. (2011), Kumbhakar et al. (2011) and Ortega-Argilés et al. (2009) have found that productivity gains from R&D investment are greater for high-tech sectors than for non-high-tech sectors. In this study productivity is measured by labor productivity. Ortega-Argilés et al. (2011) Used a longitudinal dataset of manufacturing and service firms from the United States and Europa over the period 1990-2008 and found that R&D has a positive impact on a firm's productivity. They find that the R&D coefficient is significantly larger or service and high-tech sectors in comparison with non-high-tech manufacturing sectors. Lastly, it is concluded that high-tech sectors are ahead in terms of the impact of their R&D investments on productivity. In addition, Kumbhakar et al. (2011) investigated the impact of R&D on firm efficiency as well. The efficiency of a firm is measured as labor productivity in this study and a distinction is made between high-tech, medium-tech and low-tech firms. To investigate this impact, a longitudinal dataset of top European R&D investors over the period 2000-2005 is used. They find that R&D intensity matters for a firm's efficiency, regardless of which sector it belongs to. Although, supporting R&D investment in high-tech sectors, and to a lower extent in medium tech sectors, could lead to an outward shift of the technological progress frontier, which subsequently helps to create and/or conquer new markets. This effect was not found for low-tech firms. The results concerning the low-tech sectors show that R&D is found to have a minor effect in explaining productivity. Therefore, the conclusions made in this study are that corporate R&D in high-tech sectors, and to some extent in medium-tech sectors, should be supportive. Lastly, it is stated that R&D intensity is found to be a significant factor in explaining a firm's productivity for all industries. Moreover, Ortega-Argilés et al. (2009) compare the results of this relationship across high-tech, medium-tech and low-tech sectors as well. In this study European industrial and service firms are investigated. The authors confirm the previous findings of the general positive impact of R&D on labor productivity. In addition, both at the firm and sectoral levels the R&D coefficient increases is significance and magnitude when comparing the findings of low-tech sectors with medium- and high-tech sectors. Therefore, they conclude that corporate R&D investment is more effective in high-tech sectors. Kwon and Inui (2003) tested the impact of R&D and productivity growth for Japanese manufacturing firms for the period 1995-1998. Productivity is proxied by labor productivity and a comparison between high-tech and non-high-tech firms is made. The findings show a significant role of R&D expenditure on productivity improvements, regardless of industry differences. However, they also find that the effect of R&D on productivity improvement are larger for high-tech firms than for low-tech firms. Lastly, Verspagen (1995) has investigated the role of R&D in productivity increases of firms from Europa and the United States over the period 1973-1988. In this study firm productivity is measured by the total factor productivity. He tests this role on high-tech, medium-tech and low-tech firms. The findings show that the impact of R&D on productivity is mere significant for high-tech firms.

2.1.3.3 Impact of R&D on other firm factors

Regardless of the uncertainty of assessment complications related with R&D investment, empirical studies on the impact of R&D on firm factors have increased in the last three decades. The impact of R&D is one of considerable matter in the SME performance literature, since R&D investment can set of innovations that increases firms' development. There are numerous studies in the literature that consider the role of R&D investment.

For instance, Cohen and Levinthal (1989) and De Jong and Freel (2010) investigated the impact of R&D investment on collaboration with distant organizations and concluded a positive impact of R&D on a firm's absorptive capacity. More specifically, R&D investments increases the geographically distant collaboration of a company, which denotes that the knowledge created from the relationship formed with external agents increases, when firms invest more in R&D. The capacity to effectively make use of the expanded absorptive knowledge may subsequently lead to an increase in a firm's performance.

As noted by Lefebvre et al. (1998) and Beise-Zee and Rammer (2006), R&D activities are associated with higher export performance. Investing in R&D empowers firms to increase their export performance, which subsequently contributes to making SMEs more competitive. Having a higher export performance could also help to reduce the risk associated with the firm's activities (Beise-Zee & Rammer, 2006). Another firm factor that gives SMEs higher competitive power is diversification of the activities of a firm. According to Rogers (2004), an increasement in R&D expenditure contributes to increased diversification of activities among SME's.

According to Shapiro and Titman (1986), Yasuda (2005) and Müller and Zimmermann (2009), R&D investment causes for the creation of intangible assets and subsequently leads to a higher level of risk. Shapiro and Titman (1986) stated that an increase in business risk may be caused by being more asset intensive, due to the fact that a firm's profitability is more fluctuating for highly asset intensive business. This increase in risk may cause for complications in obtaining external financing, following difficulties in increasing firm performance. Moreover, Müller and Zimmerman (2008) add that young firms with high R&D efforts, need relatively more equity financing and subsequently rely more on external financing. Investing in R&D and subsequently having the need and complications of external financing could impede the development of a firm.

Lastly, in a study on the effect of R&D intensity on corporate social responsibility, Padgett and Galán (2010) find that R&D intensity positively affects corporate social responsibility for manufacturing firms over the period 1991-2007. Based on the resource-based view, they stated that corporate social responsibility can create assets that provides a firm with competitive advantage. A higher corporate social responsibility may improve the welfare and satisfaction of stakeholders and subsequently increase firms' development.

2.1.3.4 Impact of R&D on innovation

R&D investment of a firm is contemplated as one of the principal sources of technological innovation. More specifically, R&D investment is expected to add value by generating intangible assets which may enable the acceleration of future cash flows and therefore improve the performance of a firm (Pramod et al., 2012). The following section describes empirical evidence on the impact of R&D on innovation.

Vega-Jurado, Guitiérrez-Garce, Fernandez-de-Lucio and Manjarrés-Henríquez (2008), Thornhill (2006), Bilbao-Osorio and Rodriguez-Pose (2004) and Mairesse and Mohnen (2004) have found a positive impact of R&D investment on innovation. For instance, Thornhill (2006) has investigated the impact of R&D on the level of innovation of a firm. Using survey data of Canadian manufacturing firms, he found that firms with higher aggregated levels of R&D experience higher rates of firm-level innovation. Whereas the level of innovation is measured as a binary variable, based on whether respondents had reported that their firm had introduced a national or world-first new product or not. In addition, he also tests whether firm-level innovation has an impact on revenue growth. It is found that innovative firms are more likely to enjoy higher revenue growth, without regard of the industry in which they operate. The interaction role of knowledge & training on the relation of firm-level innovation and revenue growth is investigated as well. The findings show that the interaction of firm-level knowledge assets and innovation have a positive impact on firm performance especially in high-tech industries, which means that among high-tech firms innovative products had the highest impact on revenue growth when knowledge assets were high. While the interaction of firm level training investments and innovation has a positive impact on firm performance in low-tech industries. It is concluded that the combination of training investments and innovation causes for having a higher revenue growth. Moreover, Bilbao-Osorio and Rodriguez-Pose (2004) have investigated the role of R&D investment on innovation as well, Their research has sought to determine whether R&D investment carried out by different sectors, such as private, public and higher education, have had an impact on innovation. A comparison between these different sectors is made in this research. The general results show a positive impact of R&D and innovation. They furthermore find that the impact of R&D on the rate of return is higher in the private sector than in other sectors. Nevertheless, R&D investment in the public sector is not considered to be a net contributor in the innovation process. The explanation about this finding is that public R&D is associated with basic R&D and might have a less direct link with the amount of patent applications, which is used as proxy for innovation in this study. Additionally, Mairesse and Mohnen (2004) have examined the importance of R&D for innovation. Using a dataset of French manufacturing firms, they test the impact of R&D on innovation output provided by the French CIS 3. They find that R&D is positively correlated with all the five measures of innovation output. Lastly, the impact of R&D intensity on the various measures of innovation output are different across industries. Considering the five measures of innovation output, it is concluded that innovation is more sensitive to R&D in low-tech sectors than in high-tech sectors.

Mansury and Love (2007) Have tested the impact of R&D on innovation performance in US service firms. In this study the effect of in-house R&D or outsourced R&D and formal R&D or informal R&D is tested on various measures of innovation The dependent variables used in this study are service innovation, organizational innovation, technological innovation, sales new to market and sales new/improved to firm. They find that in-house R&D has a significant positive impact on innovation, however only for formalized in-house R&D. disregarding whether R&D is outsourced or in-house, it is stated that both formal and informal R&D are significant determinants of being more innovative, whereas informal R&D is particularly significant for the introduction of services which are new to the firm, but not new to the market. Furthermore, in a comprehensive research, Vega-Jurado et al. (2008) have investigated the effect of external and internal factors on firms' product innovation, which is measured by a dummy variable that can take 3 different values. Firstly, when a firm did not introduce a new or improved product, secondly if a firm did introduce a new or improved product and was new to the firm and thirdly if a firm did introduce a new or improved product and was new to the market. Among other things, they find that a firm's technological competences, which is measured as R&D intensity, is the principal determinant of product innovation. Lastly, it is concluded that in all industry classes analyzed R&D intensity represents the most important factor in a firm's innovative performance, therefore it is concluded that the impact of R&D intensity does not vary across industries. In appendix 1 a summary on differences across studies is given in a table form.

2.2 Hypothesis development

There exists a broad scope of studies in the SME performance literature that have considered the role of R&D on firm performance. As stated in the empirical evidence chapter of this paper, there exists evidence of the positive impact of R&D on firm performance measured by various types of firm performance measures. The literature concerning the relationship of R&D on firm performance, generally describes a positive outcome, independently of taking into account of the industry in which a firm operates. Therefore, there exist a general accepted consensus that R&D has a positive impact on firm performance. Nevertheless, according to the literature, conflicting evidence is found between high-tech and non-high-tech firms regarding this relationship. The distinction between high-tech and low-tech firms on this relationship is rarely performed in the literature. In this section I will describe arguments used in this study to predict differences in impact between high-tech and non-high-tech firms.

Nunes et al. (2012) describe various factors that may cause for a greater impact of R&D on a firm's growth in high-tech SMEs, which are previously described in the empirical evidence section and are used as arguments in this study. Firstly, high-tech SMEs often experience shorter life cycle products and high costs of R&D investment that subsequently may create entry barriers and therefore decreases competition. Secondly, continuous R&D investment by high-tech SMEs may erect efficient strategies for managing corporate R&D projects, whereas non-high-tech SMEs invest occasionally in

R&D and are less likely to experience efficient management of corporate R&D projects. Hölzl (2009) adds that the effect of experience in corporate R&D processes is a principal determinant of firm performance and concludes that countries with more experience in managing R&D projects, R&D intensity has a greater impact on SME performance. Furthermore, According to Wiklund and Shepherd (2009) human resource management is considered as a principal productive factor of SMEs since human resources represents the knowledge and experience in a firm. High quality human resource management in R&D projects is a critical factor in determining the success of these projects (Lee, 2009). The third and fourth arguments are that high quality human resource management and absorptive capacity may be determinants for relatively better efficient management of R&D projects. As R&D intensity is generally higher in high-tech SMEs, the impact of R&D on firm performance is expected to be higher for these firms. Lastly, as high-tech SMEs have high levels of R&D intensity, high-tech SMEs experience greater capacity to implement complementary strategies with other firms. This may contribute to obtain benchmarking experience in R&D project management for high-tech firms.

In addition to the arguments made by Nunes et al. (2012), Kumbhakar et al. (2011) concluded that corporate R&D in high-tech sectors is more likely to lead to create and conquer new markets, whereas corporate R&D in low-tech sectors do not necessarily experience this. The market pressure confronted by a firms' R&D incentive depends essentially on its level of technological competence. Firms with high technological competence are more likely to respond aggressively. While firms with low technical competence in terms of R&D to competitive market pressure respond submissively. Therefore, R&D investments can be copied relatively easy by competitors in low-tech sectors, whereas having a high R&D intensity in high-tech sectors can function as a barrier to new firms entering the market (Lee, 2009).

As stated in the empirical evidence chapter, Chan et al. (1990) have concluded that share price responses based on R&D announcements are positively related with abnormal returns in high-tech sectors, nevertheless R&D announcements by low-tech firms are associated with negative abnormal returns. The argument used to support this finding is that investors tend to see high R&D intensive firms, such as high-tech firms, as indicators of better growth opportunities and subsequently incorporate this indication into their valuation of a firm. Szewcyzk, Tesetsekos and Zantout (1996) add that firms with better investment opportunities are more likely to make better R&D investments. Therefore, the valuation of high-tech firms may be higher than non-high-tech firms.

Lastly, Audretsch and Feldman (2004) investigated various determinants of the firm's growth rate. In their study they find that R&D is a significant factor of stimulating the growth of a firm. Furthermore, it is stated that high R&D-intensive firms, such as high-tech firms, are more likely to reach the minimum efficient scale. The minimum efficient scale is the lowest production point where the total average costs are minimized. Therefore, they conclude that high-tech firms may ensure survivability more quickly than low R&D-intensive firms.

Based on the considerations above, the theories and the empirical evidence on the impact of R&D investment on firm performance, I formulate the following Hypothesis:

The impact of R&D investment on firm performance is higher for high-tech SMEs than for non-high-tech SMEs

3. Methodology

3.1 Research Methods

This section describes the various methods used in the literature to test the impact of R&D on firm performance. Per method a brief introduction, pros and cons and how the method is applied in the literature are described. An equation section is then described and lastly, it presents the model used in this study to test the hypothesis.

3.1.2 Ordinary Least Squares (OLS)

Ordinary Least Squares (OLS) is a form of linear regression to estimate unknown parameters. Regression analysis is the most frequently used data analysis method. OLS tests the relationship between one or multiple independent variables and a dependent variable. This statistical method minimizes the sum of the squares of the difference between observed and predicted values of the dependent variable. Therefore, OLS estimates the parameters of a linear regression of a set of independent variables by minimizing the sum of the squared residuals. When certain assumptions about OLS are confirmed, this regression method creates the best possible estimates of the actual population parameters. If the assumptions are confirmed, OLS is considered as the most efficient linear regression method. This means that estimators used in the equation model are unbiased and being referred to as being efficient. Moreover, Pooled OLS is a statistical method to analyze two-dimensional panel data. Usually this means that sample data on the same individuals is collected over time (Goldberger, 1964).

OLS is the most common estimation method for linear regression. Just as any other regression analysis, OLS draws conclusion on statistical tests on a sample from a population to say something of that population. It is necessary to get the best possible estimates of the coefficients in the regression equation. Therefore, to gather the best possible estimates, there exists underlying assumptions to test whether OLS produces the best estimates of the coefficients. These assumptions are: linearity of the phenomenon measured, normality of the residuals, independence of the residuals (multicollinearity) and constant variance of the residuals (homoscedasticity). Firstly, the linearity assumption addresses the functional form of the regression. The degree to which a change in the dependent variable is associated with the independent variables. The most used method to test whether the phenomenon measured is linear is tested via scatterplots. The datapoints must be systematically distributed by a diagonal line in the scatterplot. Secondly, the normality of the residuals assumption requires that the differences between predicted and observed values are normally distributed. To test the normality of the residuals, the commonly used graphs are histograms and Q-Q-Plots. Via these graphs a visual check can be done to investigate for a distribution approximating a normal distribution. Furthermore, via a goodness-of-fit test on the residuals the normality can be tested as well. Thirdly, in a regression analysis it is assumed that each predicted value is independent. This so-called multicollinearity in the data occurs when independent variables are highly correlated with each other. Therefore, it is necessary that the predicted value of an individual is not related to any other prediction. Multicollinearity can by checked with a correlation matrix and the Variance Inflation Factor (VIF). When computing the Pearson's correlation matrix, bivariate correlations among the independent variables can be checked. The degree of the bivariate correlations should not be higher than .8. The VIF of the regression quantifies the degree that the variance in the OLS regression are increase due to multicollinearity. VIF values higher than 10 indicate that multicollinearity is high (Kutner, Nachtsheim & Neter, 2004). A value of 5 is also used therefore a VIF lower than 5 is preferable. Lastly, the constant variance of the residuals tests for homoscedasticity. The variances of the residuals should be equal for all observations. The variance should not change for each observation, this condition is known as homoscedasticity. To test if this assumption is not violated a diagnosis is made with residuals plots. Different scatterplots on residuals can be created and there should be no clear pattern in the sample distribution. If there is a clear cone-shaped pattern, there exists heteroscedasticity and the assumption is violated. Furthermore, the Levene's test for homogeneity of the variance can be executed as well. The outcome of this test results in a p-value which can be tested for significance level (Levene, 1961).

Pooled OLS is often utilized when there are no unique properties of individual observations and no universal effects across time. Since pooled OLS does not take 'within' and 'in-between' effects into account, when using unbalanced panel data this method could lead to inefficient parameters. Pooled OLS regression can be used as an unbiased estimator of parameters even when time constant attributes are presents, however fixed and random effects model are considered more efficient. Another option to use pooled OLS with unbalanced panel data is that pooled OLS can be performed with dummies for the years of the sample period. By using dummies for the years, there is no need to take time-varying-effects into account, since every year will separately be taken into account. Overall, the OLS model is a simple model and widely applicable. Therefore, it is seen as one of the best linear unbiased estimation methods. However, OLS has many assumptions about the residuals and predictors that it tends to overfit to the sample. As noted earlier, when predictors are intercorrelated the OLS model could be unstable and therefore biased.

Gui-long et al. (2017), Aggelopoulos et al. (2016), Vithessonthi and Racela (2016), Pramod et al. (2012), Ehie and Olibe (2010), Anagnostopoulous and Levis (2008) and Kwon and Inui (2003) have investigated the impact of R&D on firm performance, using the OLS regression method. Aggelopoulos et al. (2016) investigated the impact of R&D, using OLS regression method with balanced panel data. Furthermore, Vithessonthi and Racela (2016) also use OLS regression method. In their initial tests, they do not use a lagged dependent variable. However, they did test if the results would change if they made use of a lagged dependent variable, and stated that the results were mostly the same. Additionally, Anagnostopoulous and Levis (2008) used a balanced panel dataset with OLS regression method to test the impact of R&D on firm performance as well and did not further mention their reasoning behind choosing this method.

Pramod et al. (2012) test the impact of R&D on the market firm value. An unbalanced dataset is used over the period 2001-2010. Firstly, pooled OLS regression is used in this study, however they state that this model might ignore the panel structure of the data and therefore they do not find this model optimal. According to them, pooled OLS could lead to omitted variable bias. Therefore, beside pooled OLS, they also use other regression methods, which do include 'within effect' and 'between effect' estimators that explores firm specific effects and cross-sectional dimensions. In addition, Pooled OLS regression method is also used by Ehie and Olibe (2010) and Kwon and Inui (2003). Lastly, Gui-long et al. (2017) have tested the impact of R&D on the firm's profitability. In determining the impact, they did not account for a lagged dependent variable and unbalanced panel from the period 2003 to 2007 is used in this study. To test the hypotheses, pooled-OLS regressions is used. However, they state that the pooled OLS methodology is not entirely appropriate as this method leads to inefficient or asymptotically inefficient estimators. Therefore, they also use quantile regression is also in their study.

3.1.3 Fixed/Random effects

Fixed and random effects are statistical models that may be used as a linear regression method. These models are used when the data of a sample consists of panel data. The fixed effects model is a regression analysis method where the parameters are fixed variables, whereas the random effects model uses random variables. In a fixed effects regression model, the group means are fixed and in a random effects regression model the group means are a random sample from the population (Ramsey & Schafer, 2002). A fixed variable refers to a variable that is assumed to be measured without error and the values of fixed variables are assumed to wield the same values among other studies. Random variables are variables drawn from a large population and represent a random sample of possible values. Fixed and random effects models control for unobserved heterogeneity in the data over time. The fixed effects regression method is considered as the right base to conclude the most casual interpretation of the regression (Gardiner, Luo & Roman, 2009; Ramsey & Schafer, 2002).

Fixed effects regressions use demeaning, which means that for each variable the mean is calculated over time and subtracted from this variable, also called 'centering over time'. When using a fixed effects regression model, it is assumed that something within the individual may impact or causes for bias on the independent or dependent variables. This should be controlled and therefore this correlation between the individual's error term and independent variables should be removed. This model let predictors that do not vary over time fall out of the analysis. It allows individual observations that do not vary over time to fall out of the analysis as well. Thus, it uses mere information that varies over time. Therefore, fixed effects regression models are essentially designed to study the causes of changes within an individual. The logic behind this model is that something that does not vary over time, cannot affect anything over time. However, non-time-varying predictors fall from the fixed effects model and therefore no effects can be investigated on these kinds of predictors. This model uses just the variation 'within-effects' estimator. This variation may sometimes only be small part of the total and may subsequently lead to a relatively lower precision in estimation.

Unlike the fixed effects regression model that uses a separate intercept per individual, the random effects regression model uses a random intercept with a certain variance. Random effects regression models assume that the variation across individuals is assumed to be random and uncorrelated with the independent variables (Laird & Ware, 1982). Therefore, random effects regression models should be used when there is reason to believe that differences across individuals have influence on the dependent variable. An advantage of random effects is that time invariant variables can be included in the analysis (i.e. gender). In fixed effects these variables are absorbed, since they do not vary over time. However, a disadvantage is that there should be no correlation between the predictors and the variance in the model, which is called the endogeneity problem. This problem can be tested via the Durbin-Wu-Hausman test, which tests whether a fixed or random effects model should be used. In a random effects regression model the coefficients of time varying variables express both within subjects and between subjects effects. Therefore, when this assumption is confirmed, the random effects estimations are considered to be more efficient than the fixed effects estimations.

There are two common assumption made about individuals specific effects. The random effects assumption says that individual-specific effects are uncorrelated with the independent variables. moreover, the fixed effects assumption is that the individual-specific effects are correlated with the independent variables. as was stated earlier, the fixed effects regression method is considered as the right base. However, when the Durbin-Wu-Hausman test is non-significant, the random effects model may be used. The Durbin-Wu-Hausman rest evaluates the consistency of an estimator with a less efficient estimator. This test helps to test whether a statistical model corresponds with the data of the sample. (Ruud, 2000). In the case of differentiation between fixed effects and random effects regression models, random effects is preferred under the null hypothesis, since the higher efficiency. However, when the null hypothesis is false, the fixed effects model is at least as consistent and therefore preferred. Lastly, the fixed effects model procures unbiased estimations. However those estimations may be subject to high sample-to-sample variability. The random effects model will cause for bias in estimations, but this model can constrain the variance of these estimations.

Pramod et al. (2012), Kumbhakar et al. (2011), Ortega-Argilés et al. (2011) and Ortega-Argilés et al. (2009) have investigated the impact of R&D on firm performance using fixed and/or random effects methods. Ortega-Argilés et al. (2011) investigated the effect of R&D on a firm's productivity and used an unbalanced dataset over the period 1990-2008. Pooled OLS, fixed effects (FE) and random effects (RE) models are used in this study. However, in addition to Pramod et al. (2012) they also stated that the outcomes of fixed effects and random effects are more important than the pooled OLS results. According to these authors, the pooled OLS outcomes are reported for completeness of the study and the results for FE and RE are the most reliable outcomes. Furthermore, Kumbhakar et al. (2011) and Ortega-Argilés (2009) both use an unbalanced dataset. The hypothesis is tested with pooled OLS and fixed effects regressions and a comparison between both methods is made in the results chapter.

3.1.4 Generalized Method of Moments (GMM)

The generalized method of moments (GMM) is another method to estimate parameters in a regression model. This method uses 'moment conditions' to derive to certain estimators. The GMM method combines sample data with the population moment conditions to produce estimates of the unknown parameters of this model. The moment conditions are the function of the parameters to minimize a certain standard of the averages sample of the moment conditions. It constructs the estimators to maximum likelihood and is built on expected values and sample averages. GMM finds parameters values that are closest to content with the sample moment conditions. Lars Peter Hansen developed the GMM in 1982 as a generalization of the Method of Moments method, introduced by Karl Pearson in 1894 (Hansen, 1982).

The GMM method offers a way of isolating relations of interest that does not require full representation of the population. As this model provides a method for estimating parameters of a linear regression based on the information in population moment conditions, it provides a way to draw conclusions on partially specified models. The essence of GMM is to find the minimum distance solution of the parameters estimates that bring the moment conditions as close to zero as possible. Therefore, unlike maximum likelihood estimators, GMM does not require complete knowledge of the sample data. Mere specified moments derived from the population are needed for the GMM estimators. GMM is often used as a statistical tool for the analysis of financial and economic data. Furthermore, it is applied to time series, cross sectional and panel data. Advantages of the GMM model is that it can solve collinearity and in contrast to OLS, GMM can avoid overfitting. However, this model is considered as a static method and therefore it cannot discover other structures for specific samples as it has one general structure.

Nunes et al. (2012) and ho et al. (2005) have used the GMM method on their research on the impact of R&D on firm performance. Nunes et al. (2012) have used an unbalanced dynamic panel for the period 1999-2006 to test their hypotheses on the impact of R&D intensity on firm performance.

They decided, according to Arellano and Bond (1991), that firms need to be included in the sample for at least four consecutive years, to make sure that all SMEs are effectively considered. Furthermore, Nunes et al. (2012) use a probit regression model, which is a type of regression where the dependent variable is dichotomous. This regression model is used for the situation of firms leaving the market during the period of analysis in, since according to Nunes et al. (2012) this may bias the findings. The dependent variable takes the value of 1 if the firm is in the market and the value is 0 if it has left the market. Subsequently, when estimating regressions concerning the firm performance, they consider only surviving firms, where they use dynamic panel estimators (GMM system) and the inverse Mill's ratio as another independent variable to control for data bias. The GMM method is used in this study to estimate the regressions referring to the dependent variable. They state that the dynamic panel estimators of GMM has the advantages over traditional panel models, such as random effect and fixed effect models. These advantages are: 'greater control for endogeneity, greater control of possible collinearity of the independent variables and better control of the effects caused by the absence of relevant independent variables to explain the dependent variable'. Lastly, a Chow test is used to test for possible differences for each determinant as well as the overall difference for the set of determinants used in the study. Moreover, Ho et al. (2005) test the impact of R&D on firm value with an unbalanced panel dataset over a period of 40 years. They use 1 year and 3 years lag on the dependent variable and tested the hypotheses with a portfolio analysis, general method of moments (GMM) regression analysis and moderated regression analysis (MRA). They used GMM regression and corrected for heteroskedasticity, since the use of a panel dataset could introduce forms of autocorrelation into the regressions. Therefore, they correct the standard errors for induced heteroskedasticity to not overstate the significance of the coefficients estimates on the dependent variables used in this study.

3.1.5 Quantile regression

Quantile regression is another type of regressions analysis. Quantile regressions methods investigate the relationship between a set of independent variables and quantiles (specific percentiles) of the dependent variable. Therefore, this method specifies changes in quantiles of the dependent variable. Whereas, OLS regression method estimates the conditional mean of the dependent variable, quantile regression method estimates the conditional median of the dependent variable. Quantile regression methods are desired when conditional quantile functions are of interest. This model is essentially useful in applications when extreme parameters are important (Wei, Pere, Koenker & He, 2006).

The parameters in a quantile regression method estimate the change in a specific quantile of the dependent variable caused by a one unit change in the independent variable(s). Therefore, this method allows to compare different specified percentiles of the dependent variable that may be affected more by a certain independent variable than other percentiles. Quantile regression method is considered as an extension of linear regression and is often used when the conditions of linear regression are not applicable. In comparison with OLS regression methods, quantile regression methods estimates are more robust against outliers in the measurements of the dependent variable as it is measured by the median instead of the mean. As this method also gives a more complete picture of the conditional distribution when both the lower and the upper quantile are of interest in a study. Quantile regression is often used when the normality assumption for OLS is not met, since the dependent variable may be highly skewed, quantile regression is favored. Furthermore, when the interest is in individuals at the higher or lowest quantiles, such as high-intensive or low-intensive R&D firms which are investigated in this paper, the most interesting outcome can be to compare the quantile outcomes of the highest and lowest R&D intensity percentiles. Therefore, quantile regression method allows to test whether coefficients are similar across conditional quantiles. Lastly, quantile regression method is considered as consistent and robust when the error term is heteroscedastic and normally distributed. Quantile regression is considered as more robust against outliers in the measurement of the dependent variable.

Besides pooled OLS regression, Gui-long et al. (2017) also use quantile regression. They find this method more appropriate, since quantile regressions enables the examination of the whole distribution of the dependent variable. According to Gui-long et al. (2017) quantile regression techniques seem to be more appropriate in testing their hypothesis of the impact of R&D on firm performance, as they provide a robust denotation on the dependent variable, without resting on distributional assumptions. Although, where OLS regression aims at estimating the mean of the dependent variable, quantile regression results in estimates of the median or quantiles of the dependent variable. Quantile regression is also done by Falk (2010) who tests the impact of R&D on different measures of firm performance. This impact is also tested with an unbalanced panel over the period 1995-2006. According to Falk (2010), quantile regression method allows to focus on specific parts in the distribution of the dependent variable and is appropriate for detecting differences in the effect of R&D intensity at various quantiles.

3.1.6 Non-linear regression

Non-linear regressions are methods of regression where the sample data is a function which is a nonlinear combination of the model parameters by one or multiple independent variables. Non-linear regression is used when the researcher can’t find an adequate fit using linear regression or when theoretical knowledge indicates that the proper relation is non-linear. In a non-linear model functions are considered as non-linear as they cannot be written as linear in the parameters.

linear regression is considered as simpler than non-linear regression, as there is no expression for best-fitting parameters in non-linear regression methods. Non-linear functions can take various forms, examples are exponential, logarithmic, U-shaped or S-shaped forms. The non-linear regression method models the dependent variable as a function of the combination of the non-linear parameters and independent variables. In non-linear regression, the model usually takes the form of: Y=F(X,B)+E, where Y represents the dependent variable, X represents independent variables, F represents the nonlinear function, B represents the nonlinear parameters estimates and E represents the error term.

In the literature concerning the relationship between R&D intensity and firm performance various methods have been used to test whether there exists a non-linear relationship on different populations. The most commonly tested non-linear relationship are the one with a threshold, U-shaped or S-shaped relationships. For instance, Booltink et al. (2017) use a hierarchical multiple regression to test their hypothesis that R&D has an inverted u-shaped impact on firm performance of non-high-tech firms. A hierarchical linear model is used when the independent variables have a natural hierarchical structure. This method is used in this study due to the fact that a moderator effect is incorporated and metric predictor variables are measured by using different participants. Moreover, Yeh et al. (2010) use balanced panel data to test the threshold relationship of R&D and firm performance. in their study the hypotheses are tested with Hansen's (1999) advanced panel threshold regression model, which is an extension of the traditional least squared estimation method. Lastly, Wang (2009) also tests the nonlinear relationship of the impact of R&D on performance. This hypothesis is tested with a balanced panel dataset using square- and cubic- R&D intensity variables into a nonlinear regression model.

3.1.7 Equations

In OLS the relationship between the independent variables (X) and the dependent variable (Y) is estimated. The following multiple linear model equation is described to predict the value of the dependent variable:

$$Y_{it} = B_1 X_{it,1} + B_2 X_{it,2} + \cdots + E_{it}$$

where Y represents the dependent variable, X the independent variables, B the regression coefficients of the independent variables for company i at time t and E the unobserved random errors which account for influences on the dependent variable.

The equation for the fixed effects model is written as:

$$Y_{it} = B_1 X_{it,1} + A_i + \mathrm{U}_{it}$$

where Y represents the dependent variable, X the independent variables, B the regression coefficients of the independent variables, A the unknown intercept for company i at time t and U the error term.

The equation for the random effects model is written as:

$$Y_{it} = B_1 X_{it,1} + A_i + U_{it} + E_{it}$$

where Y represents the dependent variable, X the independent variables, B the regression coefficients of the independent variables, A the unknown intercept for company i at time t, U the between-effects (random effects) and E the within-effects.

The equation for the Generalized Method of Moments (GMM) model is written as:

$$\mathrm{G}(\theta 0) = \mathrm{E}[\mathrm{f}(\mathrm{Yt}, \theta 0)] = 0$$

where E denotes the expectation, Y is the generic observation, θ is a K×1 vector of the parameters and f is a dimensional vector of the functions.

The quantile regression equation could be reduced to:

$$\mathrm{Fy}\ (\mathrm{Qt}) = \mathrm{t}$$

where Qt is a certain quantile of the random variable Y.

Lastly, Non-linear equations are defined by equating to zero. For example, a non-linear equation could look like:

$$\mathrm{X2} + \mathrm{x} - 1 = 0$$

3.2 Model used in this study to test the hypothesis

In a balanced panel, the time periods are the same for all firms, whereas in an unbalanced panel there are different time periods for firms. However, having a balanced panel dataset, causes for having significant less observations in comparison with unbalanced panel data, due to SMEs leaving or ceasing to exist during the sample period. In this study an unbalanced panel dataset is used to test the hypothesis. By having an unbalanced panel, I will have more observations, which means that my sample will be larger. However, having an unbalanced panel could cause for problems of result bias, as certain individuals could be represented significantly more than other individuals. Therefore, the pooled OLS methodology is not entirely appropriate when using an unbalanced panel dataset, as this method may leads to inefficient or asymptotically estimators and could result in biased findings.

The fixed effects model and random effects model seems to be more preferable over pooled OLS. However, the majority of the studies that investigated the impact of R&D on firm performance have used the pooled OLS regression method. Pramod et al. (2012), Gui-long et al. (2017) and Ortega-Argilés et al. (2011) used Pooled OLS, however they mentioned that this method is not entirely appropriate and therefore they have also used other regression methods, such as fixed/random effects and quantile regression method. Moreover, Nunes et al. (2012) used an intermediate solution to get unbiased findings, where they had a criterion that firms should be represented a minimal amount of consecutive years in the sample period. Therefore, as most studies in the literature have used Pooled OLS and there exists multiple options to deal with the disadvantages of having an unbalanced panel, in this study Pooled OLS regression is used as the principal regression model to test my hypothesis. The sample period will consists of nine consecutive years, therefore SMEs should be a minimal of three consecutive years in the sample period.

The pooled OLS equation looks as follows:

$$\begin{aligned}\text{Firm performance}_{it} &= \beta 1(\text{R\&D intensity})_{it} + \beta 2(\text{Size})_{it} + \beta 3(\text{Age})_{it} + \beta 4(\text{Leverage})_{it} \\ &+ \beta 5(Asset\_tangiblity)_{it} + \beta 6(Industry\_control)_{it} + \varepsilon_{it}\end{aligned}$$

Where firm performance is the dependent variable, R&D intensity is the independent variable and size, age, leverage, asset tangibility and industry control are the control variables, β represents the regression coefficients of the independent variables for company i at year t And ε represents the unobserved random errors which account for influences on the dependent variable.

Utilizing Pooled OLS, different models will be constructed on the various dependent variables used in this study. Firstly, various combinations of independent variables will be tested on the dependent variable and subsequently the full model will be tested. This strategy allows me to see the change in variability when R&D intensity is added to the model. Therefore, the importance of adding R&D intensity in the model can be shown. This will subsequently be done for all dependent variables used in this study. The significance of the variables is tested against the 1%, 5% and 10% alpha levels. The regressions will be done on the full sample and on split samples. The results of the high-tech sample are compared with the non-high-tech sample results. Lastly, to test the hypothesis, the coefficient of the independent variable on the various performance variables is compared between the high-tech SME and the non-high-tech SME sample models.

Moreover, in the original regressions the dependent variables will not be lagged to test the impact of R&D on firm performance. However, as a robustness check I will also use a two-year time lag of the dependent variable to compare results with the original tests, which was done by Vithessonthi and Racela (2016) as well. In their initial tests, they do not use a lagged dependent variable. However, they did test if the results would change if they made use of a lagged dependent. Furthermore, two measures will be used for R&D intensity as a robustness check and differences between outcomes of the two measures of R&D intensity will be compared. Another robustness check is done by adding the outcome of simple quantile regression in the appendix. Since the OECD classifications, categorizes firms according to the aggregate level of R&D in a certain industry. As high aggregate levels of R&D intensity in a certain industry means that this industry is classified as high-tech, quantile regressions can be done on percentiles of R&D intensity on the various dependent variables. In this study the quantile regression estimates are considered at nine different quantiles, ranging from 0.1 to 0.9, and is done on percentiles of the dependent variables, which was used by Falk (2001) to test differences in impact of R&D on firm performance as well. As a robustness check, the difference between the highest quantile(s) and the lowest quantile(s) percentiles are investigated and compared to the findings done by the pooled OLS regression.

3.3 Variables

3.3.1 Dependent variables

As stated in the literature review chapter, the literature considering the impact of R&D on firm performance shows various measures to assess firm performance. The most common dependent variable used in studies investigating the impact of R&D on productivity gains is labor productivity, measured as value added per employee (Ortega-Argilés et al., 2011; Kumbhakar et al., 2011; Ortega-Argilés et al., 2009; Kown et al., 2003). Moreover, the most frequently used dependent variables when investigating the impact of R&D on market-based performance measures are market value (Guo et al., 2018; Booltink & Saka-Helmhout, 2018; Vithessonthi & Racela, 2016; Pramod et al., 2012; Ehie & Olibe, 2010; Lin et al., 2006; Bae & Kim, 2003) and (abnormal) share returns (Vithessonthi & Racela, 2016; Anagnostopoulous & Levis, 2008; Ho et al., 2005), where market value is most often proxied by Tobin's Q. Lastly, when the impact of R&D on operating- and accounting-based performance measures is investigated, the most common dependent variables used are ROE, ROA, profit margin and revenue growth (Guo et al., 2018; Booltink & Saka-Helmhout, 2018; Gui-long et al., 2017; Vithessonthi & Racela, 2016; Aggelopoulos et al., 2016; Lome et al., 2016; Nunes et al., 2012; Falk, 2010; Yeh et al., 2010; Wang, 2009; Anagnostopoulous & Levis, 2008).

The dependent variables used in this study are based on operating- and accounting-based performance measures. The dependent variables that will be used are ROE, ROA, revenue growth and profit margin. Based on the concerning literature, in this study ROE is measured as the ratio of net income to equity. Secondly, ROA is measured as the ratio of EBIT to total assets. Third, the revenue growth rate is defined as annual revenues of the current year minus annual revenues of the previous year to divided by annual revenues of the previous year. Lastly, profit margin is measured as EBIT divided by the operating income.

In addition, Osawa and Yamasaki (2005) investigated the time lag between initial R&D investment and the emergence of results and described that it is difficult to define the scope of the R&D results, since quantifying the value of individual R&D results is complicated. In addition, R&D results begin to unfold several years after the end of an R&D project. Therefore, it is to an increasing extent complicated to precisely grasp the total effects of R&D investment as the time lag extends. Some studies that investigated the relationship between R&D and firm performance have used lagged dependent variables (Booltink & Saka-Helmhout; Aggelopoulos et al., 2016; Lome et al., 2016, Yeh et al., 2010; Falk, 2010) However, a considerable amount of studies concerning the impact of R&D on firm performance use no lag in the dependent variable (Park et al., 2018; Guo et al., 2018; Nunes et al., 2012; Ortega-Argilés, 2011; Kumbhakar et al., 2011; Yeh et al., 2010; Ehie & Olibe, 2010; Ortega-Argilés et al., 2009) The most common reason for not using a lagged dependent variable is due to the fact that the time lag between R&D differs a lot across industries, among firms within an industry and among individual R&D projects (Lome et al., 2016; Pramod et al., 2012 Yeh et al., 2010). This could cause for variability of R&D outputs and most studies have therefore no used a lagged dependent variable (Gui-long et al., 2017). Furthermore, Yeh et al. (2010) did not adopt a lagged variable as they consider R&D intensity as an enduring commitment and a sensible approximation for past R&D efforts.

The literature shows no consistent measure to precisely grasp the effects of R&D investment on firm performance. Following the idea of Vithessonthi and Racela (2016), In this study I will use two different methods to test the relationship of R&D on firm performance and compare the results. The first method will use no lag in the dependent variables, whereas the second method will adopt a time lag of the dependent variable. Yeh et al. (2010) warn for using different lag lengths models, since it might cause for mixed research results and soften the focus. Therefore, in this study only one-time lag length model is used. Since most studies concerning the literature have logic reasoning for using no lag in the dependent variable, I will consider the model, that does not adopt lagged dependent variables as leading. Therefore, the results of the lagged dependent variables models will be compared to the model with no lagged dependent variables. Considering the literature, the time lag of the dependent variable will be 2 years, as most studies that use a lag use this time length (Booltink & Saka-Helmhout; Lome et al., 2016, Falk, 2010. Lastly, Lome et al. (2016) have specifically investigated the lag length between R&D and firm performance and concluded that the time lag from R&D investment to the corresponding revenue growth is two years. Therefore, the lag in the independent variable should take value of t-2 to explain the dependent variable at t.

3.3.2 Independent variables

The studies that have tested the relationship between R&D and firm performance have used various measurements to measure R&D. For studies investigating the productivity gains from R&D investment, R&D is often measured as R&D expenditure to the number of employees in the firm (Ortega-Argilés et al., 2011; Kumbhakar et al., 2011; Falk, 2010; Ortega-Argilés et al., 2009; Kown et al., 2003; Verspagen, 1995). Nonetheless, when firm performance is measured by market-, operating-or accounting-based performance measures, the independent variable mostly used is R&D intensity, measured as R&D expenditure to total assets (Vithessonthi & Racela, 2016; Anagnostopoulous & Levis, 2008; Lin et al., 2006), total revenues (Gui-long et al., 2017; Aggelopoulos et al., 2016; Lome et al., 2016; Nunes et al., 2012; Yeh et al., 2010; Wang, 2009; Bae & Kim, 2003; Andras & Srinivasan, 2003) or net sales (Guo et al., 2018; Pramod et al., 2012; Ehie & Olibe, 2010; Ho et al., 2005).

The other independent variable used in this study is the measure of high-tech and non-high-tech SMEs. As stated earlier, the OECD classification is used to identify high-tech and non-high-tech SMEs. There are various ways to measure this variable. For instance there are multiple studies that split their full sample in subsamples, the full sample is then split in subsamples of high-tech firms and non-high-tech or high-tech, medium-tech and low-tech firms (Aggelopoulos et al., 2016; Nunes et al., 2012; Ortega-Argilés et al., 2011; Kumbhakar et al., 2011; Ortega-Argilés et al., 2009; Anagnostopoulou & Levis, 2008; Eberhart & Maxwell, 2004; Kwon & Inui, 2003; Verspagen, 1995). Nunes et al. (2012) and Ortega-Argilés et al. (2011) used two separate samples, one for non-high-tech SMEs and one for high-tech SMEs, to test for differences in the impact of R&D intensity on firm performance between high-tech and non-high-tech SMEs. Aggelopoulos et al. (2016) and Eberhart and Maxwell (2004) used separate subsamples as well. The R&D coefficient on firm performance for high-tech SMEs was compared with the low-tech SMEs outcomes. In addition, Kumbhakar et al. (2011), Ortega-Argilés et al. (2009), Kwon and Inui (2003) and Verspagen (1995) split their full sample into three subsamples, which are high-tech, medium-tech and high-tech firms and then checked for differences in the coefficients of R&D on productivity. Anagnostopoulou and Levis (2008) investigated whether R&D-intensive firms experience higher firm performance. In this study the sample is split in subsamples as well, where the first sample consists of high R&D-intensive firms and the second sample consists of low R&D-intensive firms. However, Chan et al. (1990) used a different approach, as a dummy control variable to differentiate between high-tech and low-tech firms is used in this study taking a value of 1 when a firm is considered as high-tech and 0 when it is considered as low-tech.

Considering that the vast majority of the studies on the impact of R&D investment on industry differences have split their sample in so called subsamples, I will be using this measure to differentiate between high-tech and non-high-tech firms as well. In addition, I will also do regressions on the full sample and use the control variable High_tech to differentiate between high-tech and non-high-tech firms. The other independent variables used in this study is R&D intensity, measured as the ratio of R&D expenditure to total annual revenues. R&D intensity is also measured as R&D expenditure to total assets (R&D intensity 2) as a robustness check. However, R&D intensity measured to total annual revenues is leading.

3.3.3 Control variables

Investing in R&D is most likely to influence the firm performance. However, firm performance may be affected by other components than just R&D. The most common control variables used in studies investigating the impact of R&D on productivity gains are the firm size, firm age, time dummy, industry dummy and country dummy (Ortega-Argilés et al., 2011; Kumbhakar et al., 2011; Falk, 2010; Ortega-Argilés et al., 2009; Kown et al., 2003; Verspagen, 1995). Moreover, the most frequently used control variables when investigating the impact of R&D on market-based performance measures are firm size, firm age, leverage, industry dummy, country dummy and market-to-book value (Guo et al., 2018; Booltink & Saka-Helmhout, 2018; Vithessonthi & Racela, 2016; Pramod et al., 2012; Ehie & Olibe, 2010; Anagnostopoulous & Levis, 2008; Lin et al., 2006; Ho et al., 2005; Bae & Kim, 2003). Lastly, when the impact of R&D on operating- and accounting-based performance measures is investigated, the most common control variables used are size, age, leverage, industry dummy, country dummy and asset tangibility (Guo et al., 2018; Booltink & Saka-Helmhout, 2018; Gui-long et al., 2017; Vithessonthi & Racela, 2016; Aggelopoulos et al., 2016; Lome et al., 2016; Nunes et al., 2012; Falk, 2010; Yeh et al., 2010; Wang, 2009; Anagnostopoulous & Levis, 2008).

However, these various control variables are measured differently among the studies investigating the relationship between R&D and firm performance. For example, when productivity gains are investigated firm size is regularly measured as the number of employees (Ortega-Argilés et al., 2011; Kumbhakar et al., 2011; Falk, 2010; Ortega-Argilés et al., 2009; Kown et al., 2003; Verspagen, 1995), nevertheless when firm performance is based on operating, accounting- and market-based measures firm size is often measured as total assets (Guo et al., 2018; Vithessonthi & Racela, 2016; Anagnostopoulou & Levis, 2008; Lin et al., 2006) or total revenues (Gui-long et al., 2017; Lome et al., 2016; Nunes et al., 2012; Pramod et al., 2012; Ehie & Olibe, 2010; Yeh et al., 2010; Ho et al., 2005). Furthermore, the industry control measure is often used as a dummy variable identifying whether a firm is high-tech or non-high-tech (Lome et al., 2016; Lin et al., 2006) or to control for the distinction between manufacturing and service firms (Booltink & Saka-Helmhout 2018; Aggelopoulos et al., 2016). Leverage is in the most studies investigating the impact of R&D on firm performance measured as total liabilities divided by total assets or as the debt to equity ratio. Lastly, age is the date when the firm is established.

The control variables that I will be using in this study are firm size, firm age, leverage, asset tangibility and industry control. Firm size is measured as the logarithm of the annual revenues. Firm size could have an impact on firm performance, since larger firms may have more resources and capabilities to invest in R&D. A proxy for firm size is used in most studies that try to explain firm performance, considering that the size of a firm could have a significant influence on firm performance. Second, firm age is also considered as an important control variable in studies explaining firm performance. Therefore, I also use firm age as control variable, which is measured as the logarithm of the number of years since the date of incorporation of the firm. Third, Leverage is used as a proxy for firm risk and defined as the long-term debt divided by the total assets. This control variable tests for variation in firm valuation due to differences in the capital structure (Hawawini et al. 2003). Fourth, asset tangibility is measured as the firm's property, plant and equipment (PPE) divided by its total assets. Lastly, an industry dummy variable is used to control for industries. For the full sample high-tech SMEs take the value of one and non-high-tech SMEs the value of 0. For the split samples, industry control for high-tech SME is measured as a dummy variable, taking the value of 1 if the firm operates in the industry starting with the Nace Rev. 2 26, as this industry accounts for 77,6% of the SMEs in the high-tech sample. Industry control in the non-high-tech sample is measured as a dummy variable, taking the value of 1 if the firm operates in the industries starting with the Nace Rev 2. 20-29, as these industries account for 31,6% of the SMEs in the non-high-tech sample. Table 1 shows the variable definitions and supporting literature in table form. The descriptive statistics of the variables are presented in table 2, 3 and 4.

Variable name	Definition	Supporting literature
Dependent variables		
ROE	Net income/equity	Guo et al., 2018; Yeh et al., 2010; Wang, 2009
ROA	EBIT/total assets	Guo et al., 2018; Vithessonthi & Racela, 2016; Yeh et al., 2010; Wang, 2009
Revenue growth	(Revenues current year-revenues previous year)/(revenues previous year)	Booltink & Saka-Helmhout, 2018; Aggelopoulos et al., 2016; Lome et al., 2016; Nunes et al., 2012; Falk, 2010; Anagnostopoulous & Levis, 2008
Profit margin	EBIT/annual revenues	Booltink & Saka-Helmhout, 2018; Gui-long et al., 2017; Aggelopoulos et al., 2016; Yeh et al., 2010; Wang, 2009; Anagnostopoulous & Levis, 2008; Andras & Srinivasan, 2003
Independent variables		
R&D intensity	R&D expenditure to total revenues	Gui-long et al., 2017; Aggelopoulos et al., 2016; Lome et al., 2016; Nunes et al., 2012; Yeh et al., 2010; Wang, 2009; Bae & Kim, 2003; Andras & Srinivasan, 2003
R&D intensity 2	R&D expenditure to total assets	Vithessonthi & Racela, 2016; Anagnostopoulous & Levis, 2008; Lin et al., 2006
Control variables		
Log(Size)	Logarithm of annual revenues	Gui-long et al., 2017; Lome et al., 2016; Nunes et al., 2012; Pramod et al., 2012; Ehie & Olibe, 2010; Yeh et al., 2010; Ho et al., 2005
Log(Age)	Logarithm of the number of years since the date of incorporation of the firm	Booltink & Saka-Helmhout, 2018; Gui-long et al., 2017; Aggelopoulos et al., 2016; Lome et al., 2016; Nunes et al., 2012; Pramod et al., 2012; Falk, 2010; Wang, 2009
Leverage ratio	Long-term debt/total assets	Guo et al., 2018; Vithessonthi & Racela, 2016; Aggelopoulos et al., 2016; Nunes et al., 2012; Pramod et al., 2012; Ehie & Olibe, 2010; Yeh et al., 2010; Wang. 2009
Asset tangibility ratio	Property, plant and equipment/total assets	Vithessonthi and Racela, 2016; Aggelopoulos et al., 2016;
Full sample: High Tech control Split sample: Industry control	Dummy variable	Booltink & Saka-Helmhout (2018); Vithessonthi & Racela (2016), Aggelopoulos et al., (2016); Lome et al., (2016); Kumbhakar et al., (2011)

Table 1: Variables definition

4. Data

The data that is needed for this study, is gathered via the ORBIS database created by Bureau van Dijk, which consists extensive financial information on around 300 million private companies worldwide. Besides financial information, I need data about the number of employees and the date of the incorporation of the firms, which can be found in ORBIS. I will be using this database to collect a sample which contains the data described above from OECD countries. The sample period of studies that investigated the impact of R&D and firm performance varies between 5 and 40 years, whereas most studies use a sample period of 5 to 10 years. Based on the considerations described in the model section in the previous chapter, the sample period of this study is from 2009 to 2017.

SME data will be gathered based on the definition of the European Commission. Their definition of SME is the following: 'The category of micro, small and medium-sized enterprises (SMEs) is made up of enterprises which employ fewer than 250 persons and which have an annual turnover not exceeding EUR 50 million, and/or an annual balance sheet total not exceeding EUR 43 million' (European Commission, 2016) .

High-tech firms and non-high-tech firms are selected according to the classification of the OECD Directorate for Science, Technology and Industry (2011). Nunes (2012), Ortega-Argilés (2011), Kumbhakar (2011), Ortega-Argilés (2009) and Verspagen (1995) have used the OECD classification as well. The OECD divided this classification into 4 sub-categories: high-technology industries, medium-high-technology industries, medium-low-technology industries and low-technology industries. Before the subcategories the Nace Rev. 2 is given. High-technology industries are: (3030) Aircraft and spacecraft, (2120) Pharmaceuticals, (2620) Office, accounting and computing machinery, (2630) Radio, tv and communications equipment and (2670) Medical, precision and optical instruments.

The other three subcategories are considered as non-high-tech industries due to the fact the aggregate R&D intensity is about three times higher for the subcategory high-technology than the subcategory medium-high-technology, the difference between the high-technology subcategory and the medium-low and low is even higher, this is shown in appendix 2. Medium high-technology industries are: (27) Electrical machinery and apparatus n.e.c, (29) Motor vehicles, trailers and semi-trailers, (20) Chemicals excluding pharmaceuticals, (352 + 359) Railroad equipment and (33) transport equipment n.e.c and Machinery and equipment, n.e.c. Subsequently, Medium low-technological industries are: (3315) Building and repairing of ships and boats, (2219) Rubber and plastics products, (19) Coke, refined petroleum products and nuclear fuel, (2399) Other non-metallic mineral products and (33) Basic metals and fabricated metal products. Lastly, Low-technology industries: (3299) Manufacturing, n.e.c.; Recycling, (20-22) Wood, pulp, paper, paper products, printing and publishing, (15-16) Food products, beverages and tobacco and (17-19) Textiles, textile products, leather and footwear.

The search strategy that was used to get data from Orbis consisted of firms that are at least SME for 1 year and had also spent funds on R&D in at least 1 year of the sample period (2009-2017). The initial sample consists of 3695 firms. Firstly, 589 Firms were eliminated due to the fact that certain values are not shown or not available in both Orbis and the financial statements of the concerning SMEs. Leaving a sample of 3106 firms. Moreover, SMEs should be in the sample period for at least 3 consecutive years and should also have a minimal R&D intensity of 5% in the concerned years. 2241 Firms are eliminated that were not in the sample period for three consecutive years and have a minimal R&D intensity of 5% in these years. The full sample consists of 5003 firm years, with 1502 high-tech firms years and 3501 non-high-tech firms years.

The following data is extracted to Microsoft Excel for every year in the sample period: R&D expenditure, annual revenues, net income, EBIT, equity, operating income, long-term debt, total assets, property, plant and equipment, number of employees, country code and the corresponding industrial code per company. SMEs should be in the sample period for at least three consecutive years, therefore in Excel SMEs are deleted from the sample when this criterion does not apply. Excel is then used to split the full sample into the high-tech and non-high-tech samples.

4. Results

4.1 Descriptive statistics

Descriptive Statistics Full Sample								
	N	Minimum	Maximum	Mean	Std. Deviation	Q1	Median	Q3
ROA	5003	-0,540	0,463	0,033	0,163	-0,030	0,049	0,121
ROE	5003	-1,000	0,998	0,025	0,346	-0,061	0,076	0,187
Revenue growth	4585	-0,538	1,000	0,108	0,305	-0,069	0,069	0,224
Profit margin	5003	-0,879	0,534	0,012	0,231	-0,049	0,049	0,128
R&D intensity	5003	0,045	0,998	0,148	0,146	0,066	0,099	0,162
Asset tangibility	5003	0,001	0,739	0,168	0,182	0,025	0,089	0,268
Leverage	5003	0,000	0,600	0,112	0,136	0,010	0,059	0,166
Size (sales in millions)	5003	2,2	89,8	20,0	12,3	11,0	17,2	26,0
Age	5003	2	113	35	35	13	19	36
Descriptive Statistics High-tech Sample								
	N	Minimum	Maximum	Mean	Std. Deviation	Q1	Median	Q3
ROA	1502	-0,540	0,462	0,014	0,170	-0,066	0,035	0,113
ROE	1502	-1,000	0,998	-0,021	0,355	-0,152	0,053	0,163
Revenue growth	1368	-0,538	1,000	0,109	0,322	-0,079	0,070	0,223
Profit margin	1502	-0,879	0,534	-0,018	0,256	-0,106	0,038	0,124
R&D intensity	1502	0,045	0,998	0,166	0,175	0,070	0,105	0,181
Asset tangibility	1502	0,002	0,653	0,164	0,162	0,030	0,106	0,272
Leverage	1502	0,000	0,547	0,106	0,126	0,013	0,061	0,149
Size (sales in millions)	1502	2,2	69,4	20,7	12,5	11,5	18,2	27,2
Age	1502	2	113	33	33	14	19	33
Descriptive Statistics Non-high-tech sample								
	N	Minimum	Maximum	Mean	Std. Deviation	Q1	Median	Q3
ROA	3501	-0,485	0,463	0,041	0,160	-0,013	0,055	0,123
ROE	3501	-0,999	0,992	0,045	0,340	-0,026	0,086	0,199
Revenue growth	3217	-0,526	1,000	0,108	0,298	-0,064	0,069	0,225
Profit margin	3501	-0,763	0,514	0,024	0,218	-0,023	0,052	0,130
R&D intensity	3501	0,045	0,727	0,140	0,131	0,065	0,095	0,155
Asset tangibility	3501	0,001	0,739	0,170	0,190	0,023	0,084	0,268
Leverage	3501	0,000	0,600	0,115	0,140	0,009	0,058	0,175
Size (sales in millions)	3501	3,1	89,9	19,7	12,3	10,9	16,7	25,7
Age	3501	3	113	35	35	13	19	39

Table 2: Descriptive statistics

Descriptive Statistics High-tech Sample								
	N	Minimum	Maximum	Mean	Std. Deviation	Q1	Median	Q3
ROA	1391	-0,540	0,462	0,018	0,179	-0,071	0,040	0,123
ROE	1391	-1,000	0,998	-0,004	0,370	-0,152	0,061	0,187
Revenue growth	1260	-0,538	1,000	0,137	0,334	-0,062	0,087	0,262
Profit margin	1391	-0,879	0,534	-0,024	0,248	-0,099	0,035	0,112
R&D intensity 2	1391	0,045	0,562	0,140	0,106	0,069	0,105	0,167
Asset tangibility	1391	0,002	0,653	0,156	0,154	0,032	0,098	0,258
Leverage	1391	0,000	0,547	0,104	0,125	0,014	0,062	0,141
Size (sales in millions)	1391	2,2	69,4	21,7	13,6	11,5	18,6	29,0
Age	1391	2	113	32	33	13	18	32
Descriptive Statistics Non-high-tech Sample								
	N	**Minimum**	**Maximum**	**Mean**	**Deviation**	**Q1**	**Median**	**Q3**
ROA	3523	-0,485	0,463	0,056	0,169	-0,001	0,066	0,140
ROE	3523	-0,995	0,992	0,070	0,358	-0,010	0,109	0,242
Revenue growth	3234	-0,526	1,000	0,130	0,298	-0,005	0,048	0,117
Profit margin	3523	-0,763	0,514	0,025	0,199	-0,044	0,081	0,249
R&D intensity 2	3523	0,045	0,730	0,138	0,123	0,066	0,097	0,158
Asset tangibility	3523	0,001	0,739	0,166	0,179	0,025	0,091	0,260
Leverage	3523	0,000	0,600	0,110	0,136	0,010	0,056	0,162
Size (sales in millions)	3523	3,1	89,8	22,5	15,7	11,7	18,3	29,1
Age	3523	3	113	33	33	12	19	35

Table 3: Descriptive statistics using R&D intensity 2

Descriptive Statistics High-tech Sample								
	N	Minimum	Maximum	Mean	Std. Deviation	Q1	Median	Q3
Lagged_ROA	1046	-0,484	0,560	0,029	0,166	-0,044	0,041	0,117
Lagged_ROE	1046	-0,977	0,973	-0,005	0,337	-0,115	0,057	0,160
Lagged_Revenue growth	1046	-0,541	0,981	0,103	0,289	-0,063	0,075	0,213
Lagged_Profit margin	1046	-0,879	0,582	0,005	0,242	-0,072	0,047	0,135
R&D intensity	1046	0,045	0,994	0,159	0,164	0,069	0,103	0,178
Asset tangibility	1046	0,003	0,643	0,161	0,159	0,031	0,099	0,264
Leverage	1046	0,000	0,512	0,102	0,122	0,011	0,056	0,147
Size (sales in millions)	1046	2.2	66.3	20.3	12.3	11.4	17.7	26.0
Age	1046	2	111	32	33	13	18	32
Descriptive Statistics Non-high-tech Sample								
	N	**Minimum**	**Maximum**	**Mean**	**Deviation**	**Q1**	**Median**	**Q3**
Lagged_ROA	2529	-0,492	0,472	0,049	0,156	0,001	0,057	0,126
Lagged_ROE	2529	-0,991	1,000	0,055	0,329	-0,003	0,089	0,201
Lagged_Revenue growth	2529	-0,520	0,998	0,109	0,281	-0,053	0,072	0,220
Lagged_Profit margin	2529	-0,662	0,468	0,035	0,196	-0,004	0,055	0,129
R&D intensity	2529	0,045	0,712	0,136	0,125	0,065	0,094	0,150
Asset tangibility	2529	0,001	0,735	0,173	0,192	0,023	0,089	0,276
Leverage	2529	0,000	0,909	0,121	0,147	0,011	0,062	0,185
Size (sales in millions)	2529	2.8	95.4	19.2	12.3	10.2	16.0	25.0
Age	2529	3	111	34	34	12	18	36

Table 4: Descriptive statistics using a 2-year lag in the dependent variables

Table 2, 3 and 4 present the descriptive statistics of the variables used in this paper. The full sample consists of 5003 firm years, with 1502 high-tech firm years and 3501 non-high-tech firm years. Using R&D intensity 2, the high-tech sample consists of 1391 observations and the non-high-tech sample of

3523 observations. Using a 2-year lag in the dependent variables, the high-tech sample consists of 1046 observations and the non-high-tech sample of 2529 observations. In general, the dependent variables are greater for non-high-tech SMEs than that of high-tech SMEs. As might be expected, high-tech SMEs have, on average, a greater R&D intensity than non-high-tech SMEs have. Lastly, high-tech SMEs have, on average, (1) less asset tangibility, (2) less leverage, (3) greater size and (4) a lesser age.

The descriptive statistics are comparable with the study done by Nunes et al. (2012), as they also find that high-tech SMEs have, on average, higher R&D intensity, less leverage, greater size and a lesser age. Moreover, the ratio high-tech/non-high-tech SMEs is comparable too, whereas 30% of my full sample is high-tech in the study done by Nunes et al. (2012) 27% of the full sample is high-tech. However, they find that their dependent variable is, on average, higher for high-tech SMEs, while my dependent variables are lower for high-tech SMEs. In addition, Ortega-Argilés et al. (2011), Kumbhakar et al. (2011) and Ortega-Argilés et al. (2009) also show that R&D intensity and size are both, on average, greater for high-tech firms. Lastly, Eberhart et al. (2004) find that, on average, their dependent variable is lower for high-tech SMEs than non-high-tech SMEs.

4.2 Portfolio Analysis

	Portfolio based on R&D intensity									
	1	2	3	4	5	6	7	8	9	10
ROA	0,090	0,088	0,079	0,082	0,063	0,056	0,033	-0,005	-0,048	-0,105
	(0,072)	(0,072)	(0,069)	(0,079)	(0,065)	(0,055)	(0,050)	(0,023)	(-0,009)	(-0,071)
ROE	0,131	0,129	0,093	0,104	0,071	0,057	0,022	-0,043	-0,126	-0,185
	(0,125)	(0,118)	(0,108)	(0,117)	(0,092)	(0,086)	(0,075)	(0,040)	(-0,024)	(-0,101)
Revenue growth	0,127	0,136	0,131	0,121	0,100	0,107	0,079	0,093	0,095	0,097
	(0,070)	(0,094)	(0,076)	(0,093)	(0,070)	(0,059)	(0,061)	(0,066)	(0,054)	(0,047)
Profit margin	0,077	0,074	0,074	0,067	0,059	0,055	0,027	-0,021	-0,091	-0,204
	(0,069)	(0,068)	(0,066)	(0,062)	(0,057)	(0,052)	(0,056)	(0,032)	(-0,013)	(-0,152)
R&D intensity	0,049	0,057	0,067	0,077	0,091	0,108	0,130	0,163	0,224	0,511
	(0,049)	(0,057)	(0,066)	(0,077)	(0,091)	(0,107)	(0,129)	(0,162)	(0,220)	(0,445)
Asset tangibility	0,244	0,228	0,209	0,204	0,173	0,151	0,145	0,126	0,106	0,096
	(0,220)	(0,185)	(0,162)	(0,143)	(0,094)	(0,066)	(0,066)	(0,051)	(0,042)	(0,052)
Leverage	0,114	0,114	0,114	0,113	0,111	0,109	0,102	0,106	0,111	0,130
	(0,070)	(0,064)	(0,075)	(0,064)	(0,063)	(0,050)	(0,046)	(0,053)	(0,056)	(0,045)
Size (sales in millions)	24,1	23,5	21,8	20,3	19,8	19,6	18,9	17,9	17,3	16,6
	(22,1)	(20,7)	(17,9)	(17,1)	(17,3)	(16,6)	(15,4)	(15,1)	(14,4)	(12,9)
Age	30	32	29	27	31	35	39	44	42	38
	(19)	(17)	(18)	(18)	(19)	(19)	(19)	(23)	(25)	(19)

Table 5: Portfolios full sample. Mean value of the variable is shown. Median value is showed in the parentheses.

Table 5 shows portfolios of the full sample based on R&D intensity, starting with the lowest levels R&D intensity at column 1 to the highest levels of R&D intensity of the sample at column 10. The most important result is that the all the firm performance measures decrease when R&D intensity gets higher. For example, the average of ROA falls from 9% for the smallest R&D intensity portfolio to -10,5% for the largest R&D intensity portfolio. This shows that when portfolios are formed on R&D intensity alone, there exists a negative relation between R&D intensity and firm performance.

Moreover, asset tangibility and size decrease steadily when R&D intensity increases. Therefore, when portfolios are formed on R&D intensity alone, there exist a negative relationship between R&D intensity and asset tangibly and R&D intensity and size. Furthermore, leverage has no strong differences across portfolios. There is little spread in average leverage, as the average ranges from 10,2% to 13% over all portfolios. Therefore, there is no obvious relation between R&D intensity and leverage, when portfolios are based on R&D intensity. Lastly, the relationship between R&D intensity and age is hard to interpret. Age stays steady for the first 5 quantiles. From quantile 5 to 8 it increases steadily, however after quantile 8 age decreases again. Based on this portfolio analysis, I can’t say if there is a positive or negative relationship between R&D intensity and age.

4.3 Univariate analysis

Univariate analysis									
Differences in mean (Two-sample t-test)									
	ROA_HT - ROA	ROE_HT - ROE	Revenuegrowth_HT - Revenue growth	Profitmargin_HT - Profit margin	RDintensity_HT - R&D intensity	Assettangibility_HT - Asset tangibility	Leverage_HT - Leverage	Log_Age_HT - Log_Age	Log_Size_HT - Log_Size
T	-5,260 *	-3,635 *	-1,347	-5,509 *	5,165 *	-1,030	-2,356 *	-1,472	1,879
P-value	0,000	0,000	0,178	0,000	0,000	0,303	0,019	0,141	0,060
Differences in median (Wilcoxon signed rank test)									
	ROA_HT - ROA	ROE_HT - ROE	Revenuegrowth_HT - Revenue growth	Profitmargin_HT - Profit margin	RDintensity_HT - R&D intensity	Assettangibility_HT - Asset tangibility	Leverage_HT - Leverage	Log_Age_HT - Log_Age	Log_Size_HT - Log_Size
Z	-6,331 *	-7,781 *	-0,594	-4,893 *	-4,974 *	-1,572	-2,435 *	-1,674	-6,942 *
P-value	0,000	0,000	0,552	0,000	0,000	0,116	0,015	0,094	0,000
Differences in median (Sign test)									
	ROA_HT - ROA	ROE_HT - ROE	Revenuegrowth_HT - Revenue growth	Profitmargin_HT - Profit margin	RDintensity_HT - R&D intensity	Assettangibility_HT - Asset tangibility	Leverage_HT - Leverage	Log_Age_HT - Log_Age	Log_Size_HT - Log_Size
Z	-4,773 *	-7,096 *	-0,060	-3,793 *	-4,567 *	-2,967 *	-0,232	-2,618 *	-6,735 *
P-value	0,000	0,000	0,952	0,000	0,000	0,003	0,816	0,009	0,000

Table 6: Univariate analysis

Table 6 three univariate analysis technics to show differences in mean and median between the high-tech and non-high-tech sample. The two-sample t-test is used to compare means between the high-tech and non-high-tech sample. The Levene's test investigates whether there are different variances between the high-tech and non-high-tech sample. Equal variance is not assumed for ROA, profit margin, R&D intensity, asset tangibility, leverage, size and age. Equal variance is assumed for ROE and revenue growth. The outcomes show that the difference in the means of ROA, ROE, profit margin, R&D intensity and leverage are statistically significant. This means that ROA, ROE, profit margin and leverage are more likely to be lower for high-tech SMEs, R&D intensity is more likely to be higher. The difference in the means of revenue growth, size and age are not significant.

The Wilcoxon signed rank test is a non-parametric test to compare two related samples. The difference in the median is significant for ROA, ROE, profit margin, R&D intensity, leverage and size. The variables ROA, ROE, profit margin and leverage are more likely to have a lower value in high-tech SMEs than in non-high-tech SMEs. For R&D intensity and size these values are more likely to be higher for high-tech SMEs than for non-high-tech SMEs

The sign test is a non-parametric statistical method that tests the difference in median between two samples. The outcomes of this test are consistent with the outcomes of the Wilcoxon test. However, whereas the Wilcoxon test presented that the difference in median is not significant for asset tangibility and age, the sign test does shows that these variables are significantly different. Furthermore, it shows no significance for leverage, although the Wilcoxon test did present a significance in medians for leverage.

4.4 Regression results

4.4.1 Full sample results

4.4.1.1 Correlation tables

	ROA	ROE	Profit margin	R&D intensity	Asset tangibility	Leverage	Log_Age	Log_Size	High_tech
ROA	1,000			-0,349 *	0,045 *	-0,110 *	-0,110 *	0,174 *	-0,076 *
ROE		1,000		-0,261 *	0,033 *	-0,115 *	-0,115 *	0,129 *	-0,087 *
Profit margin			1,000	-0,393 *	0,025 *	-0,144 *	-0,096 *	0,194 *	-0,083 *
R&D intensity				1,000	-0,188 *	0,070 *	0,016	-0,177 *	0,082 *
Asset tangibility					1,000	0,228 *	-0,177 *	-0,079 *	-0,014
Leverage						1,000	-0,082 *	-0,088 *	-0,032 *
Log_Age							1,000	0,108 *	-0,021
Log_Size								1,000	0,027 *
High_tech									1,000

	Revenue growth	R&D intensity	Asset tangibility	Leverage	Log_Age	Log_Size	High_tech
Revenue growth	1,000	-0,034 *	0,005	0,050 *	-0,096 *	0,019	0,002
R&D intensity		1,000	-0,190 *	0,071 *	0,017	-0,186 *	0,073 *
Asset tangibility			1,000	0,217 *	-0,179 *	-0,071 *	-0,007
Leverage				1,000	-0,072 *	-0,076 *	-0,031 *
Log_Age					1,000	0,083 *	-0,015
Log_Size						1,000	0,028 *
High_tech							1,000

Table 7: Correlations tables full sample

4.4.1.2 OLS results

	ROA					
Model	1	2	3	4	5	6
Constant	9,10 ***	17,29 ***	-39,37 ***	-34,93 ***	16,77 ***	-34,85 ***
	(29,56)	(20,36)	(-6,87)	(-6,22)	(18,51)	(-6,15)
R&D intensity	-0,39 ***	-0,38 ***	-0,37 ***	-0,36 ***	-0,39 ***	-0,35 ***
	(-26,35)	(-25,52)	(-24,18)	(-24,11)	(-26,15)	(-23,19)
Asset tangibility			-0,01		-0,04 ***	-0,01
			(-0,62)		(-3,10)	(-0,60)
Leverage		-0,12 ***		-0,10 ***		-0,10 ***
		(-7,41)		(-6,65)		(-6,50)
Log_Age		-2,08 ***		-2,30 ***	-2,07 ***	-2,35 ***
		(-8,65)		(-9,56)	(-8,45)	(-9,69)
Log_Size			2,91 ***	3,12 ***		3,17 ***
			(8,55)	(9,29)		(9,40)
High_Tech		-1,93 ***			-1,80 ***	-2,11 ***
		(-4,12)			(-3,82)	(-4,55)
Adjusted R2	12,2%	14,4%	13,4%	15,6%	13,6%	15,9%
Observations	5003					

Table 8: ROA. R&D intensity is the ratio of R&D expenditure to total revenues. Asset tangibility is the ratio of property, plant and equipment to total assets. Leverage is the ratio of long-term debt to total assets. Log_Age is the natural logarithm of the number of years since the date of incorporation of the firm. Log_Size is the natural logarithm of the annual revenues of the firm. High_tech is a dummy variable, taking the value of 1 when the firm practices in a high-tech industry. T-values are reported in parentheses.

* statistical significance at the 10% level.

** statistical significance at the 5% level.

*** statistical significance at the 1% level.

Table 8 shows the pooled OLS regression results of the independent and control variables on ROA. The first models show how certain variables are related to ROA. The full model (6) shows how the independent and control variables are related to ROA altogether. The coefficient of R&D intensity is negative and statistically significant in all the models used. Asset tangibility has an insignificant association with firm performance. And only becomes significant when it is used in a model with R&D intensity, age and the high_tech dummy. Leverage, age and the high-tech dummy, show a statically negative relationship with firm performance, which was expected from the correlation tables, these variables keep their sign and significance no matter which model is used. Size shows a positive association with firm performance. The high-tech dummy variable shows a negative and statistically significant sign, therefore it is concluded that non-high-tech firms are more likely to have greater firm performance. The economic significance and overall model fit are comparable with the study of Booltink et al. (2018) and Aggelopoulos et al. (2016), who also perform regressions on the full sample with a dummy variable controlling for high-tech SMEs. The sign of size, leverage and asset tangibility are comparable with these studies as size has a positive impact, leverage has the same sign and low magnitude and asset tangibility has a low magnitude is often not statistically significant. In contrast to my findings. Aggelopoulos et al. (2016) confirm my finding that high-tech SMEs have lower firm performance. However, in contrast to my findings, Booltink et al. (2018) find that the high-tech dummy is positively related with firm performance and age is insignificant.

The coefficient of R&D intensity is negative in all the models on firm performance. The results of the regressions done on ROA are comparable with the regressions done on ROE and profit margin. The only outstanding difference is that asset tangibility has a significant relationship with profit margin, but not with ROE, ROA and revenue growth. Moreover, asset tangibility is only significant in one specific model which involves the R&D intensity, age and high-tech variables. in every other model asset tangibility is insignificant for the regressions done on ROE, ROA and revenue growth. Lastly, the regressions done on revenue growth show different outcomes, as the control variables size and high-tech lose their significance and leverage takes a positive and significant sign, whereas the regressions done on the other three dependent variables show that leverage has a negative and significant sign. Appendix 3 shows the results of all the regressions done on the full sample.

The knowledge-based view builds upon the difficulty to imitate knowledge-based resources, the specific and complex knowledge that is developed internally, may generate benefits in a firm. The resource-based theory is based on the thought that the firm's success is dependent on the function of resources and capabilities controlled by the firm. These theories confirm that intangible assets are likely to accomplish the necessary requirements for sustaining competitive advantage. Firms that invest in R&D could therefore experience superior firm performance, due to the fact that R&D activities lead to the development of resources which are valuable, rare, inimitable and non-substitutable resources empowers organizations to preserve competitive advantage. However, my findings show a negative and statistically significant impact of R&D investment on firm performance. Firms that invest in R&D have statistically less firm performance than firms that do not invest in R&D. The search for interdependent assets to enhance knowledge/resource capabilities and to improve innovation performance and growth causes for time and resource restrictions. Investing in R&D may therefore be subject to time compression diseconomies or exhibit decreasing returns.

The transaction cost theory refers to the cost of providing goods or services through the market. Investing in R&D involves a high degree of uncertainty considering the nature and timing of the output. Which means that investing in R&D does not necessarily result in greater output. More specifically, customer demand may fluctuate and R&D investment cannot be recouped. R&D investment often requires transaction specific investments in intangible assets that are difficult to imitate. the combination of high demand uncertainty and large R&D investment costs could subsequently cause that investing in R&D might not lead to the desired performance. R&D investment accompanied by risks are expected to have a negative effect on firm performance, as the firm faces a higher chance of financial distress. Innovative processes of a firm are filled with high risk and high uncertainty, therefore the risk should be of a negative value expect for the success of R&D investment.

According to the organizational learning theory, an organization improves over time, due to the experience it gains. The experience that is gained allows organizations to gain competitive advantage. organizational learning is a product of the organizational inquiry, which denotes that if the expected outcome differs from the actual outcome, agents in the organization will try to understand and solve this variability in outcomes. The individuals of the organization will interact with each other and organizational learning will take place. Organizational learning is a complex mechanism, which relies on the interpretations of past events. R&D activities may have difficulties making a technological breakthrough. Therefore, firm performance may be weakened with increased investment in R&D. In line with Wang (2009), the concept of lag of organizational learning on R&D activity can provide a reasonable explanation.

4.4.2 Split sample results

4.4.2.1 High-tech correlation tables

	ROA	ROE	Profit margin	R&D intensity	Asset tangibility	Leverage	Log_Age	Log_Size	Industry_control
ROA	1,000			-0,451 *	0,057 *	-0,139 *	-0,052 *	0,208 *	0,126 *
ROE		1,000		-0,330 *	0,033 *	-0,166 *	-0,035	-0,156 *	0,078 *
Profit margin			1,000	-0,565 *	0,044 *	-0,209 *	-0,042 *	0,355 *	0,166 *
R&D intensity				1,000	-0,206 *	0,188 *	0,031	-0,166 *	-0,339 *
Asset tangibility					1,000	0,151 *	-0,201 *	-0,122 *	-0,068 *
Leverage						1,000	-0,167 *	-0,068 *	-0,104 *
Log_Age							1,000	0,099 *	-0,045 *
Log_Size								1,000	0,105 *
Industry_control									1,000

	Revenue growth	R&D intensity	Asset tangibility	Leverage	Log_Age	Log_Size	Industry_control
Revenue growth	1,000	-0,025	-0,025	0,014	-0,079 *	-0,005	-0,061 *
R&D intensity		1,000	-0,211 *	0,192 *	0,039	-0,165 *	-0,335 *
Asset tangibility			1,000	0,151 *	-0,219 *	-0,128 *	-0,065 *
Leverage				1,000	-0,148 *	-0,063 *	-0,121 *
Log_Age					1,000	0,072 *	-0,043
Log_Size						1,000	0,123 *
Industry_control							1,000

Table 9: Correlations tables high-tech sample

4.4.2.2 High-tech results

	ROA					
Model	1	2	3	4	5	6
Constant	8,71 ***	12,42 ***	-46,58 ***	14,34 ***	-46,49 ***	-43,6 ***
	(16,12)	(7,94)	(-4,67)	(7,19)	(-4,77)	(-4,37)
R&D intensity	-0,44 ***	-0,43 ***	-0,44 ***	-0,46 ***	-0,40 ***	-0,42 ***
	(-19,57)	(-18,64)	(-17,63)	(-18,81)	(-17,61)	(-16,86)
Asset tangibility			-0,02	-0,06 **		-0,02
			(-0,90)	(-2,22)		(-0,96)
Leverage		-0,09 ***			-0,08 ***	-0,08 **
		(-2,75)			(-2,66)	(-2,56)
Log_Age		-0,97 **		-0,98 **	-1,24 ***	-1,36 ***
		(-2,13)		(-2,13)	(-2,75)	(-2,97)
Log_Size			3,42 ***		3,56 ***	3,55 ***
			(5,81)		(6,12)	(6,03)
Industry_control			-1,69 *	-1,66 *		-1,94 *
			(-1,69)	(-1,65)		(-1,94)
Adjusted R2	20,3%	20,7%	22,1%	20,6%	22,6%	22,7%
Observations	1502					

Table 10: ROA. R&D intensity is the ratio of R&D expenditure to total revenues. Asset tangibility is the ratio of property, plant and equipment to total assets. Leverage is the ratio of long-term debt to total assets. Log_Age is the natural logarithm of the number of years since the date of incorporation of the firm. Log_Size is the natural logarithm of the annual revenues of the firm. Industry_control is a dummy variable, taking the value of 1 when the firm practices in the Nace Rev. 2 26 industry. T-values are reported in parentheses.

* statistical significance at the 10% level.

** statistical significance at the 5% level.

*** statistical significance at the 1% level.

Table 10 shows the pooled OLS regression results of the independent and control variables on ROA. The first models show how certain variables are related to ROA. The full model (6) shows how the independent and control variables are related to ROA altogether. R&D intensity, leverage and age are significant and negatively associated with ROA, no matter which model is used. Size is positive and statistically significant in every model that was created. Just as the regressions done on the full sample, asset tangibility seems to only have a significant association with ROA, when a model with R&D intensity, age and industry control is created. Industry control is significant at the 10% level and has a negative magnitude. This means that that SMEs that perform in the industry starting with Nace Rev. 2 code 26 have a lower firm performance. The individual relationship of R&D intensity on ROA has an adjusted R^2 of 20.3%, which is the highest of all the independent variables. The full model accounts for 22,7% on how ROA is predicted, where R&D intensity predicts the biggest proportion of the variance in ROA.

The results done on ROA are comparable with ROE and profit margin. The only difference of the regressions done on the other dependent variables are that the magnitudes for age and industry control are higher. Additionally, the regressions done on revenue growth present different outcomes. The predictability of revenue growth is lower in comparison with the other dependent variables. Asset tangibility becomes significant and leverage becomes insignificant when the regressions are done on revenue growth. Appendix 4 shows the results of all the regressions done on the high-tech sample.

4.4.2.3 Non-high-tech correlation tables

	ROA	ROE	Profit margin	R&D intensity	Asset tangibility	Leverage	Log_Age	Log_Size	Industry_control
ROA	1,000			-0,284 *	0,039 *	-0,103 *	-0,139 *	0,161 *	0,094 *
ROE		1,000		-0,214 *	0,032 *	-0,099 *	-0,153 *	0,120 *	0,078 *
Profit margin			1,000	-0,272 *	0,015	-0,121 *	-0,126 *	0,167 *	0,066 *
R&D intensity				1,000	-0,185 *	0,016	0,011	-0,190 *	-0,249 *
Asset tangibility					1,000	0,253 *	-0,169 *	-0,063 *	0,446 *
Leverage						1,000	-0,050 *	-0,096 *	0,051 *
Log_Age							1,000	0,114 *	-0,137 *
Log_Size								1,000	0,075 *
Industry_control									1,000

	Revenue growth	R&D intensity	Asset tangibility	Leverage	Log_Age	Log_Size	Industry_control
Revenue growth	1,000	-0,040 *	0,018	0,065 *	-0,104 *	0,031 *	-0,004
R&D intensity		1,000	-0,185 *	0,017	0,007	-0,204 *	-0,252 *
Asset tangibility			1,000	0,239 *	-0,166 *	-0,048 *	0,443 *
Leverage				1,000	-0,045 *	-0,080 *	0,036 *
Log_Age					1,000	0,089 *	-0,137 *
Log_Size						1,000	0,093 *
Industry_control							1,000

Table 11: Correlations tables non-high-tech sample

4.4.2.4 Non-high-tech results

	ROA					
Model	1	2	3	4	5	6
Constant	8,99 ***	18,17 ***	-37,28 ***	17,23 ***	-32,25 ***	-31,92 ***
	(23,72)	(18,28)	(-5,31)	(15,85)	(-4,70)	(-4,61)
R&D intensity	-0,35 ***	-0,34 ***	-0,32 ***	-0,35 ***	-0,31 ***	-0,31 ***
	(-17,50)	(-17,58)	(-15,21)	(-17,12)	(-15,96)	(-15,36)
Asset tangibility			-0,01	-0,04 ***		-0,01
			(-0,81)	(-2,71)		(-0,39)
Leverage		-0,12 ***			-0,11 ***	-0,11 ***
		(-6,59)			(-5,95)	(-5,67)
Log_Age		-2,50 ***		-2,49 ***	-2,74 ***	-2,74 ***
		(-8,82)		(-8,59)	(-9,67)	(-9,52)
Log_Size			2,75 ***		3,05 ***	3,03 ***
			(6,60)		(7,42)	(7,32)
Industry_control			0,97	0,89		0,29
			(1,55)	(1,44)		(0,47)
Adjusted R2	8,0%	10,9%	9,2%	10,0%	12,3%	12,2%
Observations	3501					

Table 12: ROA. R&D intensity is the ratio of R&D expenditure to total revenues. Asset tangibility is the ratio of property, plant and equipment to total assets. Leverage is the ratio of long-term debt to total assets. Log_Age is the natural logarithm of the number of years since the date of incorporation of the firm. Log_Size is the natural logarithm of the annual revenues of the firm. Industry_control is a dummy variable, taking the value of 1 when the firm practices in the Nace Rev. 2 20-29 industries. T-values are reported in parentheses.

*   statistical significance at the 10% level.

**   statistical significance at the 5% level.

*** statistical significance at the 1% level.

Table 12 shows the pooled OLS regression results of the independent variables on ROA of the non-high-tech sample. The first models show how various combinations of the independent and control variables are related to ROA. The full model (6) shows how the independent and control variables are related to ROA altogether. R&D intensity, leverage and age are significant and negatively associated with ROA, Size is positive and statistically significant in every model that was created. Just as the regressions done on the full sample and the high-tech sample, asset tangibility seems to only have a significant association with ROA, when a model with R&D intensity, age and industry control is created. Industry control has no significant relationship with ROA. The individual relationship of R&D intensity on ROA has an adjusted R^2 of 8%, which is the highest of all the independent variables. The full model accounts for 12,2% on how ROA is predicted, where R&D intensity predicts the biggest proportion of the variance in ROA.

The results done on ROA are comparable with ROE and profit margin. However, just as in the high-tech sample, the regressions done on revenue growth show different outcomes. The predictability of revenue growth is lower in comparison with the other dependent variables and leverage becomes positive and statistically significant when the regressions are done on revenue growth. Appendix 4 shows the results of all the regressions done for the non-high-tech sample. The coefficient of R&D intensity is negative in every model created for all the four dependent variables for both the high-tech and non-high-tech sample. The results show a significant association for R&D intensity on all dependent variables. Moreover, the coefficient of R&D intensity of the full model is greater in the high-tech sample than in the non-high-tech sample for all the dependent variables. Whereas, the coefficient of R&D intensity on profit margin is almost the double of the non-high-tech sample in the high-tech sample. For the individual regression of R&D intensity on revenue growth, the coefficient of R&D intensity is greater in the non-high-tech sample. However, as stated earlier the results of the individual regression of R&D on revenue growth in the high-tech sample is not significant. Additionally, as the regressions on revenue growth have a low adjusted R^2 in both the high-tech and non-high-tech sample, the outcomes of the other three dependent variables are considered as more important. To test whether the R&D intensity coefficient is statistically different between samples I perform a Wald test. The Wald test shows that the coefficient of R&D intensity is statistically significant when the regressions are done on ROA (chi=5.63, p=0.02) and profit margin (chi=37.09, p=0.00). ROE (chi=1.18, p=0.28) and revenue growth (chi=0.02, p=0.89) show no statistically significant difference. Therefore, the hypothesis is only partially confirmed. Whilst the coefficient of R&D intensity is higher in the high-tech sample for ROE and revenue growth, a statistically significant difference cannot be confirmed.

The negative sign and magnitude of R&D intensity on firm performance is consistent with Vithessonthi et al. (2016), Nunes et al. (2012), Ortega-Argilés (2011), Kumbhakar (2011) and Ortega-Argilés (2009). Vithessonthi et al. (2016), find that R&D investment is negatively related with firm performance. Furthermore, in a robustness check they show that the negative sign is mostly caused by high R&D-intensive firms, as the coefficient is higher, which comes forward in my outcomes as well. Nunes et al. (2012) show a significant negative association between R&D intensity and non-high-tech SME performance, which is consistent with the results in this paper. However, they find an insignificant linear association of R&D investment on high-tech SME performance, whereas I find a significant negative association. Lastly, the finding that the coefficient of R&D intensity is higher for high-tech SMEs is consistent with Ortega-Argilés (2011), Kumbhakar (2011) and Ortega-Argilés (2009), who also find a higher coefficient for R&D for high-tech firms.

Furthermore, the adjusted R^2 is considerably greater in the high-tech sample than in the non-high-tech sample for ROA, ROE and profit margin. Industry control is never significant in the non-high-tech sample. In the high-tech sample, industry control is significant for three of the four dependent variables. Due to the fact that different industries were chosen as dummy variable for the high-tech sample and non-high-tech sample, a comparison between these results cannot be made. Although, the full sample regressions show that non-high-tech firms are more likely to have greater firm performance. Industry control shows an insignificant sign for the non-high-tech SMEs. This means that there is no significant difference between the SMEs that practice in the Nace Rev. 2 20-29 industries and the remaining industries. Industry control is significant in the high-tech-sample, this means that that SMEs that perform in the industry starting with Nace Rev. 2 code 26 have a lower firm performance than the other industries used in the high-tech sample. Moreover, asset tangibility is generally not significant in the full model for both the high-tech and the non-high-tech sample. Age is significant and negative in both samples and seems to have a greater impact for non-high-tech SMEs as the coefficient is higher for all the dependent variables. This is consistent with the outcomes of Falk (2010) and Nunes et al. (2012). Falk (2010) finds that newly founded firms are positively related with firm performance. Nunes et al. (2012) show that age is negatively associated with non-high-tech SME performance, they also show that the coefficient of age is higher for non-high-tech SMEs, however the negative sign of size on high-tech SME performance is insignificant. Additionally, size shows a significant and positive sign and has a greater impact on high-tech SMEs. This outcome is consistent with Guo et al. (2018), as they show a positive sign of size in general and Booltink et al. (2018), as they show a positive sign of size on non-high-tech SME performance. Moreover, leverage is comparable between the two samples, as the negative coefficient of leverage between samples do not differ a lot. This result is consistent with the studies of Guo et al. (2018) and Aggelopoulos et al. (2016), as they also show that leverage is negatively related with firm performance. Lastly, the overall model fit is comparable with Nunes et al. (2012), Vithessonthi et al. (2016) and Ortega-Argilés et al. (2011), as they find similar percentages for the high-tech sample and non-high-tech sample. The difference in overall model fit is also comparable with Nunes et al. (2012), as they show that the overall model fit is higher for the high-tech sample.

4.4.3 Robustness results: Outcomes with R&D intensity 2

4.4.3.1 High-tech correlation tables

	ROA	ROE	Profit margin	R&D intensity 2	Asset tangibility	Leverage	Log_Age	Log_Size	Industry_control
ROA	1,000			-0,343 *	0,065 *	-0,138 *	-0,061 *	0,220 *	0,154 *
ROE		1,000		-0,289 *	0,062 *	-0,167 *	-0,050 *	0,164 *	0,095 *
Profit margin			1,000	0,311 *	0,078 *	-0,208 *	-0,060 *	0,245 *	0,218 *
R&D intensity 2				1,000	-0,204 *	0,071 *	-0,013	-0,066 *	-0,199 *
Asset tangibility					1,000	0,163 *	-0,224 *	-0,130 *	-0,034
Leverage						1,000	-0,165 *	-0,067 *	-0,113 *
Log_Age							1,000	0,062 *	-0,053 *
Log_Size								1,000	0,114 *
Industry_control									1,000

	Revenue growth	R&D intensity 2	Asset tangibility	Leverage	Log_Age	Log_Size	Industry_control
Revenue growth	1,000	-0,021	0,020	0,016	-0,105 *	0,020	-0,043
R&D intensity 2		1,000	-0,207 *	0,074 *	-0,005	-0,034	-0,192 *
Asset tangibility			1,000	0,166 *	-0,237 *	-0,133 *	-0,029
Leverage				1,000	-0,144 *	-0,060 *	-0,132 *
Log_Age					1,000	0,031	-0,054 *
Log_Size						1,000	0,133 *
Industry_control							1,000

Table 13: Correlations tables high-tech sample

4.4.3.2 High-tech results

	ROA					
Model	1	2	3	4	5	6
Constant	9,91 ***	17,03 ***	-78,02 ***	10,90 ***	-67,60 ***	-70,26 ***
	(13,25)	(9,33)	(-7,16)	(4,68)	(-6,32)	(-6,44)
R&D intensity 2	-0,58 ***	-0,57 ***	-0,52 ***	-0,56 ***	-0,55 ***	-0,52 ***
	(-13,61)	(-13,40)	(-12,03)	(-12,56)	(-13,19)	(-11,94)
Asset tangibility			0,03	-0,02		0,03
			(1,15)	(-0,53)		(1,10)
Leverage		-0,18 ***			-0,17 ***	-0,17 ***
		(-5,06)			(-4,74)	(-4,60)
Log_Age		-1,76 ***		-1,30 **	-1,97 ***	-1,77 ***
		(-3,43)		(-2,49)	(-3,92)	(-3,44)
Log_Size			5,04 ***		5,09 ***	5,04 ***
			(7,80)		(8,03)	(7,86)
Industry_control			3,12 ***	3,72 ***		2,37 **
			(2,80)	(3,27)		(2,13)
Adjusted R2	11,7%	13,6%	16,0%	12,7%	17,4%	17,6%
Observations	1391					

Table 14: ROA. R&D intensity is measured as R&D expenditure to total assets. Asset tangibility is the ratio of property, plant and equipment to total assets. Leverage is the ratio of long-term debt to total assets. Log_Age is the natural logarithm of the number of years since the date of incorporation of the firm. Log_Size is the natural logarithm of the annual revenues of the firm. Industry_control is a dummy variable, taking the value of 1 when the firm practices in the Nace Rev. 2 26 industry. T-values are reported in parentheses.

* statistical significance at the 10% level.

** statistical significance at the 5% level.

*** statistical significance at the 1% level.

Table 14 shows the results of the regressions done on ROA using R&D intensity 2. In general, R&D intensity, leverage age and size keep their sign and significant. The predictability of the dependent variables decreases when R&D intensity 2 is used. The only great difference with the original results is that industry control takes a positive and statistically significant sign when R&D intensity 2 is used, whereas the original results generally show a negative and statistically sign.

In comparison with the original results, measuring R&D intensity as R&D expenditure to total assets causes for a higher magnitude of the R&D intensity coefficient both in the individual and full model for ROE, ROA and revenue growth. Besides the lower coefficient of R&D on profit margin, the adjusted R^2 is considerably lower as well. Changing from 31.9% in the original results to 9.7% in the robustness check, which explains why the full model has a lower adjusted R^2 (20.3%) than the original results on profit margin (36.1%). The regressions on revenue growth still present a low adjusted R^2. Lastly, the most outstanding differences are the changes in the regressions on profit margin. Asset tangibility and industry control have a significant negative association of the full model in the original results, however these outcomes show a significant positive association with profit margin when R&D is measured as R&D expenditure to total assets. Appendix 5 shows the results of all the regressions done on the high-tech sample with R&D intensity 2.

4.4.3.3 Non-high-tech correlation tables

	ROA	ROE	Profit margin	R&D intensity 2	Asset tangibility	Leverage	Log_Age	Log_Size	Industry_control
ROA	1,000			-0,171 *	0,049 *	-0,120 *	-0,128 *	0,195 *	0,120 *
ROE		1,000		-0,119 *	0,053 *	-0,117 *	-0,135 *	0,157 *	0,109 *
Profit margin			1,000	-0,174 *	0,046 *	-0,127 *	-0,112 *	0,169 *	0,089 *
R&D intensity 2				1,000	-0,163 *	-0,001	-0,058 *	-0,119 *	-0,261 *
Asset tangibility					1,000	0,275 *	-0,177 *	-0,029	0,433 *
Leverage						1,000	-0,056 *	-0,100 *	0,082 *
Log_Age							1,000	0,078 *	-0,104 *
Log_Size								1,000	0,112 *
Industry_control									1,000

	Revenue growth	R&D intensity 2	Asset tangibility	Leverage	Log_Age	Log_Size	Industry_control
Revenue growth	1,000	0,009	0,051 *	0,053 *	-0,146 *	0,047 *	0,033 *
R&D intensity 2		1,000	-0,159 *	0,006	-0,060 *	-0,129 *	-0,259 *
Asset tangibility			1,000	0,259 *	-0,175 *	-0,015	0,431 *
Leverage				1,000	-0,046 *	-0,084 *	0,068 *
Log_Age					1,000	0,051 *	-0,104 *
Log_Size						1,000	0,131 *
Industry_control							1,000

Table 15: Correlations tables non-high-tech sample

4.4.3.4 Non-high-tech results

	ROA					
Model	1	2	3	4	5	6
Constant	8,84 ***	19,43 ***	-64,44 ***	16,37 ***	-54,32 ***	-53,85 ***
	(21,03)	(17,56)	(-9,25)	(13,47)	(-7,90)	(-7,80)
R&D intensity 2	-0,23 ***	-0,25 ***	-0,18 ***	-0,22 ***	-0,22 ***	-0,20 ***
	(-10,27)	(-10,97)	(-7,80)	(-9,57)	(-9,81)	(-8,52)
Asset tangibility			0,04	-0,03 **		0,01
			(0,25)	(-1,98)		(0,81)
Leverage		-0,16 ***			-0,14 ***	-0,15 ***
		(-7,87)			(-6,91)	(-7,16)
Log_Age		-2,81 ***		-2,62 ***	-3,04 ***	-2,87 ***
		(-8,92)		(-8,11)	(-9,77)	(-9,06)
Log_Size			4,29 ***		4,42 ***	4,29 ***
			(10,37)		(10,87)	(10,51)
Industry_control			2,26 ***	2,77 ***		1,80 ***
			(3,43)	(4,20)		(2,78)
Adjusted R2	2,9%	6,4%	6,3%	5,2%	9,4%	9,7%
Observations	3523					

Table 16: ROA. R&D intensity is measured as R&D expenditure to total assets. Asset tangibility is the ratio of property, plant and equipment to total assets. Leverage is the ratio of long-term debt to total assets. Log_Age is the natural logarithm of the number of years since the date of incorporation of the firm. Log_Size is the natural logarithm of the annual revenues of the firm. Industry_control is a dummy variable, taking the value of 1 when the firm practices in the Nace Rev. 2 20-29 industries. T-values are reported in parentheses.

* statistical significance at the 10% level.

** statistical significance at the 5% level.

*** statistical significance at the 1% level.

Comparing with the original results, in the high-tech sample the coefficient of R&D becomes greater when R&D intensity is measured as R&D expenditure to total assets, in the non-high-tech sample the coefficient become lower. The adjusted R^2 are generally lower as well in the robustness results. R&D intensity, asset tangibility, leverage, age and size keep their sign and significance. The only difference with the original results is that industry control becomes significant. In general, the outcomes of the coefficients, significance and adjusted R^2 of this robustness check are consistent with the original results. The sign and magnitude of the R&D coefficient is comparable with Vithessonthi et al. (2016) and Lin et al. (2006). The overall model fit is not comparable with similar studies. However, different values are found for the overall model fit, as Vithessonthi et al. (2016) find values of 50%, however Anagnostopoulou et al. (2008) find values below 5%.

The regressions on revenue growth still present a low adjusted R^2. R&D intensity stays significant for the regressions done on ROE and profit margin, although the regression of R&D intensity on revenue growth become insignificant. Consistent with the original results, the coefficient of R&D intensity is higher in the high-tech sample on all the four dependent variables, all models considered. A Wald test is performed and in contrast to the original results, the difference between the

R&D intensity coefficient on ROE becomes significant (chi=21.61, p=0.00). The coefficient is also statistically significant different when the regressions are done on ROA (chi=22.96, p=0.00) and profit margin (chi=15,61, p=0.00). The difference of the coefficient on revenue growth (chi=1.54, p=0.21) stays insignificant. As the regressions done on ROE, ROA and profit margin are considered as more important than the regressions done on revenue growth, the hypothesis can be confirmed. Appendix 5 shows the results of all the regressions done on the non-high-tech sample with R&D intensity 2.

4.4.4 Robustness results: Outcomes with lag in the dependent variables

4.4.4.1 High-tech correlation tables

	LAG_ROA	LAG_ROE	LAG_Profit margin	R&D intensity	Asset tangibility	Leverage	Log_Age	Log_Size	Industry_control
LAG_ROA	1,000			-0,225 *	0,065 *	-0,012	-0,044	0,027	0,046
LAG_ROE		1,000		0,043	0,030	0,025	-0,033	-0,182 *	-0,106 *
LAG_Profit margin			1,000	-0,315 *	0,055 *	-0,108 *	-0,021	0,109 *	0,072 *
R&D intensity				1,000	-0,190 *	0,205 *	0,043	-0,151 *	-0,318 *
Asset tangibility					1,000	0,165 *	-0,215 *	-0,140 *	-0,107 *
Leverage						1,000	-0,179 *	-0,063 *	-0,090 *
Log_Age							1,000	0,097 *	-0,042
Log_Size								1,000	0,085 *
Industry_control									1,000

	LAG_Revenue growth	R&D intensity	Asset tangibility	Leverage	Log_Age	Log_Size	Industry_control
LAG_Revenue growth	1,000	0,043	0,030	0,025	-0,033	-0,182 *	-0,106 *
R&D intensity		1,000	-0,190 *	0,205 *	0,043	-0,151 *	-0,318 *
Asset tangibility			1,000	0,165 *	-0,215 *	-0,140 *	-0,107 *
Leverage				1,000	-0,179 *	-0,063 *	-0,090 *
Log_Age					1,000	0,097 *	-0,042
Log_Size						1,000	0,085 *
Industry_control							1,000

Table 17: Correlations tables high-tech sample

4.4.4.2 High-tech results

Model	Lagged ROA 1	2	3	4	5	6
Constant	6,56 ***	7,84 ***	8,57	9,21 ***	9,27	9,41
	(9,39)	(3,98)	(0,66)	(3,60)	(0,74)	(0,72)
R&D intensity	-0,23 ***	-0,23 ***	-0,23 ***	-0,23 ***	-0,23 ***	-0,24 ***
	(-7,48)	(-7,46)	(-6,93)	(-7,04)	(-7,39)	(-6,96)
Asset tangibility			0,02	0,01		0,01
			(0,56)	(0,34)		(0,17)
Leverage		0,04			0,04	0,04
		(0,98)			(0,98)	(0,90)
Log_Age		-0,53		-0,61	-0,53	-0,53
		(-0,92)		(-1,05)	(-0,90)	(-0,89)
Log_Size			-0,09		-0,09	-0,04
			(-0,11)		(-0,12)	(-0,05)
Industry_control			-1,01	-1,11		-1,11
			(-0,77)	(-0,84)		(-0,84)
Adjusted R2	5,0%	5,0%	4,8%	4,9%	4,9%	4,8%
Observations	1046					

Table 18: ROA. R&D intensity is measured as R&D expenditure to total revenues. Asset tangibility is the ratio of property, plant and equipment to total assets. Leverage is the ratio of long-term debt to total assets. Log_Age is the natural logarithm of the number of years since the date of incorporation of the firm. Log_Size is the natural logarithm of the annual revenues of the firm. Industry_control is a dummy variable, taking the value of 1 when the firm practices in the Nace Rev. 2 26 industry. T-values are reported in parentheses.

* statistical significance at the 10% level.

** statistical significance at the 5% level.

*** statistical significance at the 1% level.

Comparing these results with the original results, the coefficient of R&D intensity stays negative and statistically significant, however the economic significant decreases. Furthermore, all the control variables lose their significance and the adjusted R^2 decreases from 22,7% in the original results to 4,8% when using a 2-year lag in the dependent variable.

considering the other models in appendix 6, the first thing that is outstanding is that the adjusted R^2 decreases considerably, although the adjusted R^2 for revenue growth more than doubles. Furthermore, the coefficient of R&D intensity is lower for both the individual and the full models. The significance and negative sign of R&D intensity is consistent with the original results. Furthermore, all the control variables lose their significance in the full model when the 2-year lag is implemented in the dependent variables. only size keeps its significance when a lag is implemented for revenue growth and profit margin. Appendix 6 shows the results of all the regressions done on the high-tech sample using a 2-year lag in the dependent variables.

4.4.4.3 Non-high-tech correlation tables

	LAG_ROA	LAG_ROE	LAG_Profit margin	R&D intensity	Asset tangibility	Leverage	Log_Age	Log_Size	Industry_control
LAG_ROA	1,000			-0,201 *	0,072 *	-0,054 *	-0,084 *	0,092 *	0,125 *
LAG_ROE		1,000		-0,153 *	0,066 *	-0,046 *	-0,107 *	0,046 *	0,099 *
LAG_Profit margin			1,000	-0,173 *	0,053 *	-0,081 *	-0,075 *	0,091 *	0,086 *
R&D intensity				1,000	-0,179 *	0,020	0,004	-0,183 *	-0,254 *
Asset tangibility					1,000	0,252 *	-0,168 *	-0,083 *	0,460 *
Leverage						1,000	-0,066 *	-0,112 *	0,065 *
Log_Age							1,000	0,151 *	-0,136 *
Log_Size								1,000	0,052 *
Industry_control									1,000

	LAG_Revenue growth	R&D intensity	Asset tangibility	Leverage	Log_Age	Log_Size	Industry_control
LAG_Revenue growth	1,000	0,020	0,068 *	0,041 *	-0,060 *	-0,217 *	0,041 *
R&D intensity		1,000	-0,179 *	0,020	0,004	-0,183 *	-0,254 *
Asset tangibility			1,000	0,252 *	-0,168 *	-0,083 *	0,460 *
Leverage				1,000	-0,066 *	-0,112 *	0,065 *
Log_Age					1,000	0,151 *	-0,136 *
Log_Size						1,000	0,052 *
Industry_control							1,000

Table 19: Correlations tables non-high-tech sample

4.4.4.4 Non-high-tech results

	Lagged ROA					
Model	1	2	3	4	5	6
Constant	8,31 ***	13,66 ***	-16,58 **	11,29 ***	-12,83	-14,31 *
	(18,55)	(11,69)	(-2,06)	(8,90)	(-1,61)	(-1,78)
R&D intensity	-0,25 ***	-0,25 ***	-0,21 ***	-0,23 ***	-0,23 ***	-0,21 ***
	(-10,31)	(-10,28)	(-8,26)	(-9,13)	(-9,51)	(-8,23)
Asset tangibility			0,01	-0,05		0,02
			(0,61)	(-0,26)		(0,86)
Leverage		-0,06 ***			-0,05 **	-0,06 ***
		(-2,89)			(-2,54)	(-2,90)
Log_Age		-1,51 ***		-1,29 ***	-1,67 ***	-1,48 ***
		(-4,48)		(-3,78)	(-4,94)	(-4,31)
Log_Size			1,41 ***		1,61 ***	1,59 ***
			(2,94)		(3,35)	(3,30)
Industry_control			2,42 ***	2,35 ***		2,06 ***
			(3,28)	(3,20)		(2,80)
Adjusted R2	4,0%	4,9%	4,8%	5,0%	5,3%	5,7%
Observations	2529					

Table 20: ROA. R&D intensity is measured as R&D expenditure to total revenues. Asset tangibility is the ratio of property, plant and equipment to total assets. Leverage is the ratio of long-term debt to total assets. Log_Age is the natural logarithm of the number of years since the date of incorporation of the firm. Log_Size is the natural logarithm of the annual revenues of the firm. Industry_control is a dummy variable, taking the value of 1 when the firm practices in the Nace Rev. 2 20-29 industries. T-values are reported in parentheses.

* statistical significance at the 10% level.

** statistical significance at the 5% level.

*** statistical significance at the 1% level.

Consistent with the results in the high-tech sample, when comparing these results with the original results, the economic significance of R&D intensity and adjusted R^2 decreases when using a 2-year lag for ROA. In contrast with the high-tech sample, the control variables keep their sign and significance. Industry control becomes significant in these results. The sign and magnitude of R&D intensity is comparable with previous studies. However, the low overall model fit is not comparable with previous studies. Vithessonthi et al. (2016) have used a 2-year lag to test the relationship between R&D investment and ROA and found that the overall model fit varies between 50%-60%. Other studies that used a 2-year lag in the dependent variable(s) show that the overall model fit varies between 10%-20% (Booltink et al., 2018; Ehie et al., 2010).

Consistent with the outcomes of the high-tech sample, when using a 2-year lag in the dependent variables, the adjusted R^2 decreases considerably, although the adjusted R^2 for revenue growth more than doubles. Furthermore, the coefficient of R&D intensity is lower as well, both in the individual and the full models. The significance and negative sign of R&D intensity is consistent with the original results. In contrast to the outcomes of the high-tech sample, the non-high-tech sample outcomes are consistent with the original results. The adjusted R^2 is considerably lower than the original results and most independent variables lose their significance in the high-tech sample in this robustness check. A Wald test is performed to test whether the R&D intensity coefficient is different between the two samples. In contrast to the original results, the coefficient is not statistically different for ROA (chi=0.30, p=0.58), ROE (chi=0.02, p=0.88) and revenue growth (chi=0.05, p=0.82). Consistent with the previous results, the R&D intensity coefficients are statistically significant different from each other when the regression is done on profit margin (chi=22.14, p=0.00). Based on these results, the hypothesis cannot be confirmed for ROA, ROE and revenue growth. Appendix 6 shows the results of all the regressions done on the non-high-tech sample using a 2-year lag in the dependent variables.

4.4.4 Quantile regression outcomes

4.4.4.1 High-tech results

	ROA							
Quantile	Q1	Q2	Q3	Q4	Q5	Q7	Q8	Q9
Constant	-118,30 ***	-58,80 ***	-36,15 ***	-21,25 *	-14,17	-14,27	-20,95 *	-15,15
	(-4.93)	(-3,81)	(-3,13)	(-1,83)	(-1,60)	(-1,24)	(-1,73)	(-0,99)
R&D intensity	-0,63 ***	-0,64 ***	-0,57 ***	-0,42 ***	-0,36 ***	-0,33 ***	-0,32 ***	-0,31 ***
	(-10,47)	(-16,58)	(-19.80)	(-14,27)	(-16,16)	(-11,53)	(-10,40)	(-7,91)
Asset tangibility	0,06	0,40	0,01	0,01	-0,02	-0,06 **	-0,10 ***	0,15 ***
	(0,92)	(1,00)	(0.41)	(0,31)	(-0,74)	(-2,16)	(-3,06)	(-3,82)
Leverage	-0,03	-0,10 **	-0,04	-0,06 *	-0,08 ***	-0,15 ***	-0,14 ***	-0,18 ***
	(-0,35)	(-2,01)	(-1.21)	(-1,68)	(-2,82)	(-4,12)	(-3,73)	(-3,69)
Log_Age	-2,44 **	-2,07 ***	-1,29 **	-1,62 ***	-1,34 ***	-1,77 ***	-1,49 ***	-1,69 **
	(-2,22)	(-2,92)	(-2.44)	(-3,04)	(-3,30)	(-3,35)	(-2,69)	(-2,40)
Log_Size	7,22 ***	4,16 ***	2,85 ***	2,06 ***	1,73 ***	2,20 ***	2,78 ***	2,96 ***
	(5,11)	(4,57)	(4.20)	(3,01)	(3,30)	(3,25)	(3,90)	(3,27)
Industry_control	-2,28	-2,87 *	-2,68 **	-1,32	-0,97	-0,57	-0,47	-2,47
	(-0,95)	(-1,86)	(-2,32)	(-1,13)	(-1.10)	(-0,49)	(-0,38)	(-1,61)
Pseudo R2	19,5%	17,5%	15,7%	13,2%	11,6%	10,2%	10,1%	9,9%
Observations	1502							

Table 21: Quantile regression: ROA. R&D intensity is measured as R&D expenditure to total revenues. Asset tangibility is the ratio of property, plant and equipment to total assets. Leverage is the ratio of long-term debt to total assets. Log_Age is the natural logarithm of the number of years since the date of incorporation of the firm. Log_Size is the natural logarithm of the annual revenues of the firm. Industry_control is a dummy variable, taking the value of 1 when the firm practices in the Nace Rev. 2 26 industry. T-values are reported in parentheses.

*   statistical significance at the 10% level.

**   statistical significance at the 5% level.

*** statistical significance at the 1% level.

4.4.4.2 Non-high-tech results

Quantile	Q1	Q2	Q3	Q4	Q5	Q7	Q8	Q9
	ROA							
Constant	-20,72	-20,95 **	-21,97 ***	-23,24 ***	-25,42 ***	-24,13 ***	-18,05 *	-32,02 ***
	(-1,06)	(-2,01)	(-2,96)	(-3,73)	(-4,68)	(-3,67)	(-1,88)	(-2,77)
R&D intensity	-0,69 ***	-0,64 ***	-0,43 ***	-0,29 ***	-0,23 ***	-0,15 ***	-0,17 ***	-0,18 ***
	(-12,02)	(-20,83)	(-19,42)	(-15,69)	(-14,37)	(-7,95)	(-5,86)	(-5,41)
Asset tangibility	0,07	0,02	0,01	0,00	0,00	-0,04 ***	-0,08 ***	-0,12 ***
	(1,60)	(0,68)	(0,55)	(0,12)	(-0,21)	(-2,88)	(-3,56)	(-4,78)
Leverage	-0,12 **	-0,06 **	-0,07 ***	-0,06 ***	-0,07 ***	-0,11 ***	-0,14 ***	-0,17 ***
	(-2,18)	(-2,12)	(-3,30)	(-3,77)	(-4,96)	(-5,92)	(-5,37)	(-5,53)
Log_Age	-3,68 ***	-3,26 ***	-2,56 ***	-2,04 ***	-2,20 ***	-2,53 ***	-2,77 ***	-3,65 ***
	(-4,54)	(-7,52)	(-8,27)	(-7,89)	(-9,75)	(-9,23)	(-6,94)	(-7,61)
Log_Size	1,73	2,18 ***	2,20 ***	2,24 ***	2,52 ***	2,80 ***	2,78 ***	4,24 ***
	(1,49)	(3,51)	(4,95)	(6,03)	(7,78)	(7,12)	(4,86)	(6,15)
Industry_control	0,98	-1,06	-0,52	-0,32	-0,56	-0,01	0,40	0,67
	(0,57)	(-1,15)	(-0,79)	(-0,57)	(-1,.17)	(-0,02)	(0,47)	(0,65)
Pseudo R2	12,3%	10,5%	7,7%	6,1%	5,5%	5,5%	6,1%	7,9%
Observations	3501							

Table 22: Quantile regression: ROA. R&D intensity is measured as R&D expenditure to total revenues. Asset tangibility is the ratio of property, plant and equipment to total assets. Leverage is the ratio of long-term debt to total assets. Log_Age is the natural logarithm of the number of years since the date of incorporation of the firm. Log_Size is the natural logarithm of the annual revenues of the firm. Industry_control is a dummy variable, taking the value of 1 when the firm practices in the Nace Rev. 2 20-29 industries. T-values are reported in parentheses.

* statistical significance at the 10% level.

** statistical significance at the 5% level.

*** statistical significance at the 1% level.

R&D intensity has a steady significant and negative coefficient over all the quartiles for both samples, with an exception for the quantile regressions done on revenue growth. Asset tangibility seems to have a significant negative association with certain dependent variables but only in the highest quantiles. Which means that asset tangibility only plays a significant role when firm performance becomes greater. The sign of asset tangibility is consistent between samples. Leverage and age have a constant significant negative association with the dependent variables over all quartiles, except for the quantile regressions done on revenue growth. Size has a very inconsistent sign over the quantile regressions. Size is consistent with a significant and positive coefficient in almost all the quantiles for both samples. Lastly, industry control is mostly insignificant over the quantiles in both samples.

The results in appendix 7 are consistent with the results of table 22. However, size has a different sign over the quantiles. For ROE in the high-tech sample, size is positive and significant in only the first few quantiles, while for the non-high-tech sample size is insignificant at the first two quantiles but significant in the other quantiles. For revenue growth, size is positive and significant in the first quantiles and the last quantiles, however the quantiles close to the median are insignificant in both samples. For profit margin, size is positive and significant for the first few quartiles, but becomes insignificant in the highest quantiles for both samples. Furthermore, industry control is mostly insignificant over the quantiles in both samples. However, for revenue growth, industry control shows a significant and negative sign in the first quartiles for both samples. Lastly, the Pseudo R^2 decreases when quantiles are becoming larger.

Not considering the quantile regressions done on revenue growth (as the pseudo R^2 are low and coefficients are insignificant), the coefficient of R&D intensity is greater in the non-high-tech sample for the first two quantiles. The coefficient of R&D intensity seems to decrease as quantiles become larger in the high-tech sample. However, the coefficient of R&D intensity decreases at a much higher rate when quantiles become larger in the non-high-tech sample. The Wald test was performed on the coefficient of R&D intensity over all quantiles to test whether there is a statistical difference between samples, after quantile 3, the R&D intensity coefficient is statistically higher in the high-tech sample for all the dependent variables. Appendix 7 the results of all the quantile regressions done on the high-tech and non-high-tech sample.

5. Conclusion and discussion

Considering two samples of high-tech SMEs and non-high-tech SMEs (1502 high-tech firm years and 3501 non-high-tech firm years), by using pooled OLS regression based on a pooled dataset, this paper analyses the difference in the linear relationship between R&D investment and firm performance in high-tech SMEs and non-high-tech SMEs. In this section the answer will be given on the following research question: Do high tech SMEs experience superior performance in comparison with non-high-tech SMEs, based on R&D intensity? I use ROE, ROA, revenue growth and profit margin as proxies for firm performance and R&D intensity as the proxy for R&D investment. Additionally, a discussions based on the results will be presented.

I identify a similar relationship between R&D intensity and firm performance in high-tech SMEs and non-high-tech SMEs, as the pooled OLS regression show the same negative and statistically significant relationship between R&D intensity and firm performance. The robustness checks that consider a different measure for R&D intensity and a 2-year lag in the dependent variables confirm the original results. The quantile regressions show that R&D intensity is negative and statistically significant over all the quantiles. Therefore, R&D investment is a determinant that restricts firm performance in both high-tech SMEs and non-high-tech SMEs.

The coefficient of R&D intensity on firm performance is higher in the high-tech sample. The Wald test for equal coefficients show that the difference of the R&D intensity coefficient is statistically different for the regressions done on two of the four firm performance measures. When R&D intensity 2 is used, the R&D intensity coefficient is statistically different for three of the four firm performance measures. Therefore, the hypothesis has been confirmed and the research question can consequently be answered. High-tech SMEs do not experience superior performance in comparison with non-high-tech SMEs, as the coefficient of R&D intensity on firm performance is greater for high-tech SMEs, it restricts the firm performance greater for these SMEs. The negative sign of R&D intensity attributes to the uncertainty and risk associated with investments in R&D. The consensus that R&D investments need time to reap the rewards of innovation outputs is contradicted, as the robustness check with a 2-year lag in the dependent variables shows the same negative and statistically significant sign. Lastly, smaller, older and higher leveraged SMEs are found to restrict firm performance more quickly than bigger, younger and less leveraged SMEs, for both high-tech and non-high-tech SMEs. However, firm age has a greater impact in non-high-tech SMEs and firm size has a greater impact in high-tech SMEs.

A few limitations need to be taken into consideration regarding my results. Firstly, I conducted research on high-tech and non-high-tech SMEs from OECD countries, using the ORBIS database. Although the high-tech sample and non-high-tech sample does include cases from each OECD country, few countries are underrepresented. Therefore, I recognize that I cannot ensure full representativeness. Therefore, caution needs to be exercised when generalizing my results. Future research could consider increasing sample generalizability by increasing country representativeness of the sample.

Second, the literature on the impact of R&D investment on firm performance shows both evidence for a negative and positive relationship. My findings of a negative linear relationship between R&D investment and firm performance is concordant with earlier results (Vithessonthi et al., 2016; Aggelopoulos et al., 2016; Nunes et al., 2012). Although, there also exists evidence concerning a positive linear relationship between R&D investment and firm performance. The nature of the relationship between R&D investment and firm performance remains elusive. Therefore, my results increase the need for future research on the topic of R&D concerning performance to precisely grasp the impact of R&D investment on firm performance.

Third, This study uses no lag length to identify the impact of R&D intensity on firm performance, although as a robustness check a 2-year lag is implemented on the dependent variables. the impact of R&D intensity on firm performance may be time-lagged. As R&D investment varies among industries, companies within an industry and among R&D projects (Lome et al., 2016; Pramod et al., 2012 Yeh et al., 2010), it is complicated to set a certain time lag as this may be unavailing. This is the most common argument, that researchers used no time lag in their research on the impact of R&D investment on firm performance. Future research should realize a comprehensive framework to identify the time lag of R&D investment on firm performance among industries, companies within an industry and among R&D projects.

Appendix 1: Differences across prior studies

Dependent variable	Literature	Method(s)	Sample	Period
Market-based				
Market value (Q ratio)	Guo, Wang and Wei (2018)	OLS	Chinese listed manufacturing firms	2009-2016
	Vithessonthi and Racela (2016)	OLS	Financial firms that listed on U.S. stock exchanges	1990–2013
	Pramod, Krishnan and Puja (2012)	Pooled OLS	Indian manufacturing firms	2001-2010
	Lin, Lee and Hung (2006)	Multilevel statistical methods	U.S.-based technology public firms	1985-1999
	Bae and Kim (2003)	Cross-sectional regression model	U.S., German and Japanese firms	1996-1998
	Deeds (2001)	A linear regression model	Newly public pharmaceutical biotechnology companies	1982-1993
	Booltink and Saka-Helmhout (2018)	Hierarchical multiple regression	Manufacturing and service SMEs from all 28 EU member countries	2007-2012
	Ehie and Olibe (2010)	Pooled OLS	Manufacturing and service U.S. firms	1990–2007
Stock returns	Vithessonthi and Racela (2016)	OLS	Financial firms that listed on U.S. stock exchanges	1990–2013
	Anagnostopoulou and Levis (2008)	OLS	U.K. listed nonfinancial firms	1990–2003
	Ho, Keh and Ong (2005)	GMM and MRA regression	Manufacturing and non-manufacturing United States firms	1962–2001
Operating- and accounting-based	**Literature**	**Method(s)**	**Sample**	**Period**
ROE	Guo, Wang and Wei (2018)	OLS	Chinese listed manufacturing firms	2009-2016
	Yeh, Chua, Sher and Chiu (2010)	Hansen’s advanced panel threshold model	Publicly traded Taiwan information technology and electronic firms	1999–2004

	Wang (2009)	Square- and cubic- R&D intensity into a nonlinear regression model	Top high-tech manufacturing firms from Taiwan	2001-2008
ROA	Guo, Wang and Wei (2018)	OLS	Chinese listed manufacturing firms	2009-2016
	Vithessonthi and Racela (2016)	OLS	Financial firms that listed on U.S. stock exchanges	1990–2013
	Yeh, Chua, Sher and Chiu (2010)	Hansen’s (1999) advanced panel threshold regression model	Publicly traded Taiwan information technology and electronic firms	1999–2004
	Wang (2009)	Square- and cubic- R&D intensity into a nonlinear regression model	Top high-tech manufacturing firms from Taiwan	2001-2008
ROS	Vithessonthi and Racela (2016)	OLS	Financial firms that listed on U.S. stock exchanges	1990–2013
	Wang (2009)	Square- and cubic- R&D intensity into a nonlinear regression model	Top high-tech manufacturing firms from Taiwan	2001-2008
Profitability	Gui-long, Yi, Kai-hua and Jiang (2017)	pooled-OLS and pooled-quantile regressions	China’s electronics manufacturing firms	2003-2007
	Booltink and Saka-Helmhout (2018)	Hierarchical multiple regression	Manufacturing and service SMEs from all 28 EU member countries	2007-2012
	Aggelopoulos, Georgopoulos and Tsamis (2016)	OLS	Greek SMEs	2002-2007

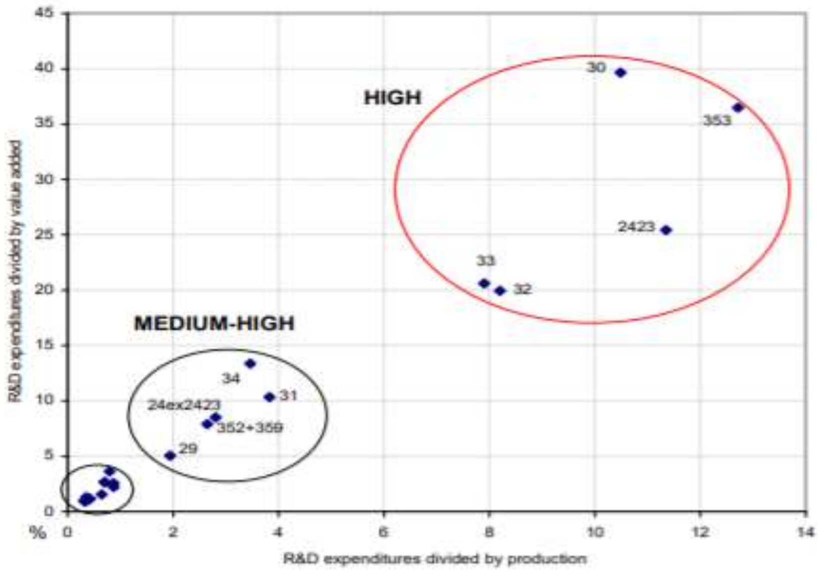
	Wang (2009)	Square- and cubic- R&D intensity into a nonlinear regression model	Top high-tech manufacturing firms from Taiwan	2001-2008
	Andras and Srinivasan (2003)	OLS and GLS	Consumer product and manufacturing product companies	2000
Cash flows	Aggelopoulos, Georgopoulos and Tsamis (2016)	OLS	Greek SMEs	2002-2007
Growth rates	Aggelopoulos, Georgopoulos and Tsamis (2016)	OLS	Greek SMEs	2002-2007
	Lome, Heggeseth and Moen (2016)	Binary logistic regression model	Norwegian manufacturing SMEs	1999–2009
	Nunes, Serrasqueiroa and Leitão (2012)	Probit and GMM regression models	Portuguese manufacturing SMEs	1999–2006
	Falk (2010)	LAD and quantile regressions	Austrian manufacturing and service firms	1995–2006
	Yeh, Chua, Sher and Chiu (2010)	Hansen's advanced panel threshold model	Publicly traded Taiwan information technology and electronic firms	1999–2004
	Wang (2009)	Square- and cubic- R&D intensity into a nonlinear model	Top high-tech manufacturing firms from Taiwan	2001-2008
	Anagnostopoulou and Levis (2008)	OLS	U.K. listed nonfinancial firms	1990–2003
Productivity-based	**Literature**	**Method(s)**	**Sample**	**Period**
labor productivity (value added per employee)	Ortega-Argilés, Piva and Vivarelli (2011)	Pooled OLS, FE and RE	U.S. and European manufacturing and service firms	1990-2008
	Kumbhakar, Ortega-Argilés, Potters,	Pooled OLS and RE	Top European R&D investors	2000–2005

	Vivarelli and Voigt (2011)			
	Ortega-Argilés, Piva, PottersS and Vivarell (2009)	Pooled OLS and RE	Top European R&D investors	1991–2002
	Kwon and Inui (2003)	Pooled OLS	Japanese Manufacturing Firms	1995-1998
Total factor productivity	Verspagen (1995)	OLS	Manufacturing firms from 9 principal OECD countries	1973-1988
Other firm factors	**Literature**	**Method(s)**	**Sample**	**Period**
Risk	Müller and Zimmermann (2009)	Tobit regression model	German manufacturing and service SMEs	2003
	Yasuda (2005)	A regression model	Japanese manufacturing firms	1992 and 1995
Absorptive capacity	De Jong and Freel (2010)	Multilevel regressions models	Dutch high-tech small firms	2006
	Cohen and Levinthal (1989)	A regression model	Non R&D performing business units and performing R&D business units	1975-1977
Innovation	Vega-Jurado, Guitiérrez-Garce, Fernandez-de-Lucio and Manjarrés-Henríquez (2008)	Non-parametric statistics	Industrial SMEs from Spain	2001–2003
	Thornhill (2006)	OLS, logistic and weighted Heckman regressions	Canadian manufacturing firms	1999 and 2000
	Mansury and Love (2007)	Probit and tobit regression models	U.S. service firms	2004
	Bilbao-Osorio and Rodriguez-Pose (2004)	OLS	EU firms	1990-1998

	Mairesse and Mohnen (2004)	Probit and tobit regression models	French manufacturing firms	1998-2000
Diversification	Rogers (2004)	OLS and WLS	Australian Manufacturing and non-manufacturing SMEs	1994–1995 and 1996–1997
Export performance	Beise-Zee and Rammer (2006)	Probit and tobit regression models	German manufacturing and service firms	1999
	Lefebvre, Lefebvre and Bourgault (1998)	Tobit regression model	Canadian SMEs	1990

Appendix 2: Aggregate R&D intensity on industry level

Annex 1.1. Aggregate R&D intensity of selected OECD countries, 1997



Annex 1.2. Aggregate R&D intensity of selected OECD countries, 1997: zoom on medium-low and low groups

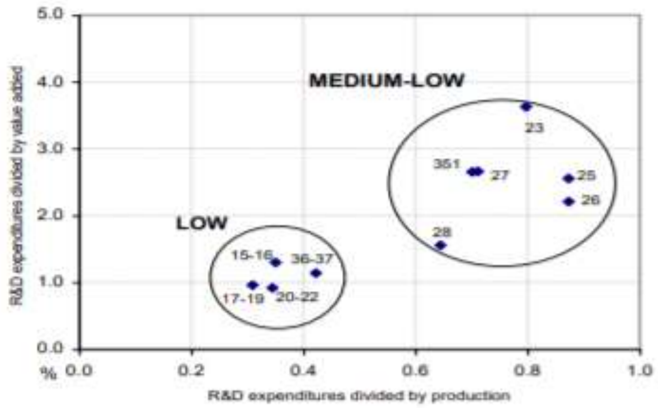


Figure 1: Aggregate R&D intensity (OECD STI Scoreboard, 2001).

Appendix 3: Outcomes full sample

	ROA					
Model	1	2	3	4	5	6
Constant	9,10 ***	17,29 ***	-39,37 ***	-34,93 ***	16,77 ***	-34,85 ***
	(29,56)	(20,36)	(-6,87)	(-6,22)	(18,51)	(-6,15)
R&D intensity	-0,39 ***	-0,38 ***	-0,37 ***	-0,36 ***	-0,39 ***	-0,35 ***
	(-26,35)	(-25,52)	(-24,18)	(-24,11)	(-26,15)	(-23,19)
Asset tangibility			-0,01		-0,04 ***	-0,01
			(-0,62)		(-3,10)	(-0,60)
Leverage		-0,12 ***		-0,10 ***		-0,10 ***
		(-7,41)		(-6,65)		(-6,50)
Log_Age		-2,08 ***		-2,30 ***	-2,07 ***	-2,35 ***
		(-8,65)		(-9,56)	(-8,45)	(-9,69)
Log_Size			2,91 ***	3,12 ***		3,17 ***
			(8,55)	(9,29)		(9,40)
High_Tech		-1,93 ***			-1,80 ***	-2,11 ***
		(-4,12)			(-3,82)	(-4,55)
Adjusted R2	12,2%	14,4%	13,4%	15,6%	13,6%	15,9%

	ROE					
Model	1	2	3	4	5	6
Constant	11,67 ***	30,71 ***	-64,00 ***	-52,93 ***	28,90 ***	-53,65 ***
	(17,34)	(16,58)	(-5,09)	(-4,30)	(14,61)	(-4,32)
R&D intensity	-0,62 ***	-0,58 ***	-0,59 ***	-0,56 ***	-0,61 ***	-0,54 ***
	(-19,09)	(-18,11)	(-17,48)	(-17,20)	(-18,84)	(-16,30)
Asset tangibility			-0,01		-0,07 ***	-0,01
			(-0,47)		(-2,70)	(-0,23)
Leverage		-0,28 ***		-0,26 ***		-0,26 ***
		(-8,10)		(-7,42)		(-7,39)
Log_Age		-4,73 ***		-5,04 ***	-4,63 ***	-5,14 ***
		(-9,01)		(-9,56)	(-8,66)	(-9,68)
Log_Size			4,54 *	4,95 ***		5,12 ***
			(6,09)	(6,72)		(6,94)
High_Tech		-5,53 ***			-5,21 ***	-5,83 ***
		(-5,42)			(-5,08)	(-5,74)
Adjusted R2	6,8%	9,6%	7,4%	9,9%	8,6%	10,4%

	Revenue growth					
Model	1	2	3	4	5	6
Constant	11,88 ***	20,73 ***	0,70	0,49	23,20 ***	3,88
	(18,54)	(11,49)	(0,06)	(0,04)	(12,07)	(0,31)
R&D intensity	-0,07 **	-0,07 **	-0,06 **	-0,06 **	-0,07 **	-0,08 **
	(-2,27)	(-2,41)	(-2,01)	(-2,05)	(-2,38)	(-2,43)
Asset tangibility			0,01		-0,03	-0,05 *
			(0,03)		(-1,30)	(-1,88)
Leverage		0,10 ***		0,11 ***		0,12 ***
		(3,13)		(3,21)		(3,56)
Log_Age		-3,19 ***		-3,26 ***	-3,42 ***	-3,42 ***
		(-6,24)		(-6,36)	(-6,60)	(-6,58)
Log_Size			0,67	1,22 *		1,10
			(0,90)	(1,67)		(1,49)
High_Tech		0,29			0,18	0,25
		(0,29)			(0,18)	(0,25)
Adjusted R2	0,1%	1,1%	0,1%	1,2%	1,0%	1,4%

	Profit margin					
Model	1	2	3	4	5	6
Constant	10,38 ***	21,59 ***	12,37 ***	-57,85 ***	21,20 ***	-56,06 ***
	(24,25)	(18,35)	(21,62)	(-7,44)	(16,85)	(-7,16)
R&D intensity	-0,62 ***	-0,60 ***	-0,63 ***	-0,57 ***	-0,64 ***	-0,57 ***
	(-30,26)	(-29,36)	(-30,12)	(-27,84)	(-30,42)	(-27,15)
Asset tangibility			-0,07 ***		-0,09 ***	-0,04 **
			(-3,88)		(-5,23)	(-2,15)
Leverage		-0,22 ***		-0,20 ***		-0,19 ***
		(-9,94)		(-9,13)		(-8,58)
Log_Age		-2,64 ***		-2,96 ***	-2,67 ***	-3,12 ***
		(-7,91)		(-8,91)	(-7,87)	(-9,31)
Log_Size			-2,57 ***	4,75 ***		4,76 ***
			(-3,92)	(10,21)		(10,22)
High_Tech		-2,93 ***			-2,68 ***	-3,20 ***
		(-4,52)			(-4,11)	(-4,99)
Adjusted R2	15,5%	18,1%	15,9%	19,5%	16,9%	19,9%

Appendix 4: Outcomes split samples

High-tech sample

ROA						
Model	1	2	3	4	5	6
Constant	8,71 ***	12,42 ***	-46,58 ***	14,34 ***	-46,49 ***	-43,6 ***
	(16,12)	(7,94)	(-4,67)	(7,19)	(-4,77)	(-4,37)
R&D intensity	-0,44 ***	-0,43 ***	-0,44 ***	-0,46 ***	-0,40 ***	-0,42 ***
	(-19,57)	(-18,64)	(-17,63)	(-18,81)	(-17,61)	(-16,86)
Asset tangibility			-0,02	-0,06 **		-0,02
			(-0,90)	(-2,22)		(-0,96)
Leverage		-0,09 ***			-0,08 ***	-0,08 **
		(-2,75)			(-2,66)	(-2,56)
Log_Age		-0,97 **		-0,98 **	-1,24 ***	-1,36 ***
		(-2,13)		(-2,13)	(-2,75)	(-2,97)
Log_Size			3,42 ***		3,56 ***	3,55 ***
			(5,81)		(6,12)	(6,03)
Industry_control			-1,69 *	-1,66 *		-1,94 *
			(-1,69)	(-1,65)		(-1,94)
Adjusted R2	20,3%	20,7%	22,1%	20,6%	22,6%	22,7%

ROE						
Model	1	2	3	4	5	6
Constant	9,03 ***	17,38 ***	-76,15 ***	19,46 ***	-72,54 ***	-69,44 ***
	(7,58)	(5,06)	(-3,44)	(4,42)	(-3,37)	(-3,15)
R&D intensity	-0,67 ***	-0,62 ***	-0,68 ***	-0,72 ***	-0,62 ***	-0,63 ***
	(-13,54)	(-12,42)	(-12,42)	(-13,32)	(-11,69)	(-11,38)
Asset tangibility			-0,06	-0,11 **		-0,04
			(-1,05)	(-1,98)		(-0,64)
Leverage		-0,33 ***			-0,33 ***	-0,32 ***
		(-4,64)			(-4,68)	(-4,51)
Log_Age		-1,83 *		-1,49	-2,37 **	-2,48 **
		(-1,84)		(-1,47)	(-2,38)	(-2,45)
Log_Size			5,38 ***		5,71 ***	5,59 ***
			(4,12)		(4,43)	(4,30)
Industry_control			-4,09 *	-4,05 *	-4,41 **	-4,62 **
			(-1,85)	(-1,81)	(-2,02)	(-2,09)
Adjusted R2	10,8%	12,0%	12,0%	11,1%	13,3%	13,2%

Revenue growth						
Model	1	2	3	4	5	6
Constant	11,67 ***	20,45 ***	28,45	31,54 ***	22,75	36,57
	(9,74)	(5,80)	(1,23)	(7,04)	(1,00)	(1,57)
R&D intensity	-0,05	-0,04	-0,12 **	-0,12 **	-0,04	-0,13 **
	(-0,91)	(-0,83)	(-2,14)	(-2,22)	(-0,84)	(-2,27)
Asset tangibility			-0,09	-0,13 **		-0,13 **
			(-1,62)	(-2,31)		(-2,36)
Leverage		0,02			0,02	0,03
		(0,25)			(0,24)	(0,44)
Log_Age		-2,88 ***		-3,55 ***	-2,88 ***	-3,48 ***
		(-2,81)		(-3,43)	(-2,80)	(-3,33)
Log_Size			-0,55		-0,14	-0,32
			(-0,40)		(-0,10)	(-0,24)
Industry_control			-6,45 ***	-6,99 ***		-6,92 ***
			(-2,90)	(-3,15)		(-3,11)
Adjusted R2	0,0%	0,5%	0,5%	1,0%	0,4%	1,2%

Profit margin						
Model	1	2	3	4	5	6
Constant	12,00 ***	17,91 ***	-84,46 ***	21,29 ***	-87,24 ***	-79,22 ***
	(15,94)	(8,27)	(-6,14)	(7,68)	(-6,52)	(-5,79)
R&D intensity	-0,83 ***	-0,80 ***	-0,83 ***	-0,88 ***	-0,76 ***	-0,80 ***
	(-26,53)	(-25,17)	(-24,43)	(-25,74)	(-24,05)	(-23,22)
Asset tangibility			-0,09 ***	-0,14 ***		-0,08 **
			(-2,61)	(-4,09)		(-2,27)
Leverage		-0,23 ***			-0,23 ***	-0,21 ***
		(-5,25)			(-5,19)	(-4,87)
Log_Age		-1,29 **		-1,28 **	-1,79 ***	-2,09 ***
		(-2,05)		(-2,01)	(-2,88)	(-3,33)
Log_Size			6,02 ***		6,36 ***	6,21 ***
			(7,42)		(7,96)	(7,70)
Industry_control			-2,88 **	-2,77 **		-3,30 **
			(-2,09)	(-1,97)		(-2,41)
Adjusted R2	31,9%	33,1%	34,9%	32,7%	35,8%	36,1%

Non-high-tech sample

ROA

Model	1	2	3	4	5	6
Constant	8,99 ***	18,17 ***	-37,28 ***	17,23 ***	-32,25 ***	-31,92 ***
	(23,72)	(18,28)	(-5,31)	(15,85)	(-4,70)	(-4,61)
R&D intensity	-0,35 ***	-0,34 ***	-0,32 ***	-0,35 ***	-0,31 ***	-0,31 ***
	(-17,50)	(-17,58)	(-15,21)	(-17,12)	(-15,96)	(-15,36)
Asset tangibility			-0,01	-0,04 ***		-0,01
			(-0,81)	(-2,71)		(-0,39)
Leverage		-0,12 ***			-0,11 ***	-0,11 ***
		(-6,59)			(-5,95)	(-5,67)
Log_Age		-2,50 ***		-2,49 ***	-2,74 ***	-2,74 ***
		(-8,82)		(-8,59)	(-9,67)	(-9,52)
Log_Size			2,75 ***		3,05 ***	3,03 ***
			(6,60)		(7,42)	(7,32)
Industry_control			0,97	0,89		0,29
			(1,55)	(1,44)		(0,47)
Adjusted R2	8,0%	10,9%	9,2%	10,0%	12,3%	12,2%

ROE

Model	1	2	3	4	5	6
Constant	12,31 ***	33,68 ***	-60,66 ***	31,60 ***	-49,43 ***	-48,84 ***
	(14,95)	(15,60)	(-3,97)	(13,40)	(-3,30)	(-3,24)
R&D intensity	-0,56 ***	-0,55 ***	-0,50 ***	-0,56 ***	-0,50 ***	-0,50 ***
	(-12,95)	(-12,97)	(-11,14)	(-12,68)	(-11,70)	(-11,24)
Asset tangibility			-0,02	-0,08 **		-0,01
			(-0,65)	(-2,42)		(-0,31)
Leverage		-0,25 ***			-0,23 ***	-0,23 ***
		(-6,35)			(-5,85)	(-5,59)
Log_Age		-5,92 ***		-5,88 ***	-6,32 ***	-6,31 ***
		(-9,61)		(-9,35)	(-10,23)	(-10,05)
Log_Size			4,33 ***		5,03 ***	4,98 ***
			(4,76)		(5,61)	(5,54)
Industry_control			2,15	1,72		0,61
			(1,59)	(0,20)		(0,46)
Adjusted R2	4,5%	7,8%	5,2%	6,9%	8,6%	8,6%

Revenue growth

Model	1	2	3	4	5	6
Constant	12,07 ***	21,22 ***	-10,36	24,09 ***	-10,39	-9,86
	(15,73)	(10,30)	(-0,70)	(10,72)	(-0,71)	(-0,67)
R&D intensity	-0,09 **	-0,09 **	-0,08 *	-0,10 **	-0,07 *	-0,09 **
	(-2,25)	(-2,28)	(-1,94)	(-2,53)	(-1,79)	(-2,23)
Asset tangibility			0,04	0,01		-0,01
			(1,21)	(0,31)		(-0,40)
Leverage		0,13 ***			0,14 ***	0,14 ***
		(3,52)			(3,67)	(3,73)
Log_Age		-3,37 ***		-3,58 ***	-3,49 ***	-3,68 ***
		(-5,74)		(-5,98)	(-5,91)	(-6,14)
Log_Size			1,34		1,90 **	1,97 **
			(1,51)		(2,17)	(2,24)
Industry_control			-1,63	-2,05		-1,99
			(-1,28)	(-1,63)		(-1,57)
Adjusted R2	0,1%	1,5%	0,2%	1,2%	1,6%	1,7%

Profit margin

Model	1	2	3	4	5	6
Constant	8,78 ***	20,82 ***	-57,90 ***	20,24 ***	-50,92 ***	-49,92 ***
	(16,87)	(15,25)	(-6,02)	(13,54)	(-5,40)	(-5,26)
R&D intensity	-0,46 ***	-0,45 ***	-0,42 ***	-0,47 ***	-0,41 ***	-0,42 ***
	(-16,73)	(-16,79)	(-14,87)	(-16,80)	(-15,14)	(-14,98)
Asset tangibility			-0,03	-0,07 ***		-0,02
			(-1,50)	(-3,39)		(-0,80)
Leverage		-0,19 ***			-0,18 ***	-0,17 ***
		(-7,72)			(-7,06)	(-6,57)
Log_Age		-3,15 ***		-3,23 ***	-3,49 ***	-3,59 ***
		(-8,09)		(-8,11)	(-8,98)	(-9,09)
Log_Size			4,01 ***		4,34 ***	4,33 ***
			(7,02)		(7,69)	(7,64)
Industry_control			0,33	0,28		-0,62
			(0,38)	(0,33)		(-0,73)
Adjusted R2	7,4%	10,4%	8,7%	9,2%	11,8%	11,8%

Appendix 5: Robustness outcomes with R&D intensity 2

High-tech sample

ROA						
Model	1	2	3	4	5	6
Constant	9,91 ***	17,03 ***	-78,02 ***	10,90 ***	-67,60 ***	-70,26 ***
	(13,25)	(9,33)	(-7,16)	(4,68)	(-6,32)	(-6,44)
R&D intensity 2	-0,58 ***	-0,57 ***	-0,52 ***	-0,56 ***	-0,55 ***	-0,52 ***
	(-13,61)	(-13,40)	(-12,03)	(-12,56)	(-13,19)	(-11,94)
Asset tangibility			0,03	-0,02		0,03
			(1,15)	(-0,53)		(1,10)
Leverage		-0,18 ***			-0,17 ***	-0,17 ***
		(-5,06)			(-4,74)	(-4,60)
Log_Age		-1,76 ***		-1,30 **	-1,97 ***	-1,77 ***
		(-3,43)		(-2,49)	(-3,92)	(-3,44)
Log_Size			5,04 ***		5,09 ***	5,04 ***
			(7,80)		(8,03)	(7,86)
Industry_control			3,12 ***	3,72 ***		2,37 **
			(2,80)	(3,27)		(2,13)
Adjusted R2	11,7%	13,6%	16,0%	12,7%	17,4%	17,6%

ROE						
Model	1	2	3	4	5	6
Constant	13,84 ***	28,62 ***	-121,09 ***	18,17 ***	-97,23 ***	-103,68 ***
	(8,75)	(7,45)	(-5,18)	(3,68)	(-4,27)	(-4,45)
R&D intensity 2	-1,01 ***	-0,98 ***	-0,94 ***	-1,00 ***	-0,95 ***	-0,92 ***
	(-11,26)	(-11,00)	(-10,11)	(-10,58)	(-10,75)	(-9,90)
Asset tangibility			0,07	-0,02		0,09
			(1,03)	(-0,25)		(1,32)
Leverage		-0,47 ***			-0,45 ***	-0,47 ***
		(-6,24)			(-6,00)	(-6,08)
Log_Age		-3,37 ***		-2,25 **	-3,68 ***	-3,37 ***
		(-3,12)		(-2,02)	(-3,44)	(-3,07)
Log_Size			7,86 ***		7,56 ***	7,77 ***
			(5,67)		(5,60)	(5,68)
Industry_control			2,34	3,23		0,50
			(0,98)	(1,34)		(0,21)
Adjusted R2	8,3%	11,0%	10,3%	8,5%	12,9%	12,9%

Revenue growth						
Model	1	2	3	4	5	6
Constant	14,57 ***	26,96 ***	-6,13	32,66 ***	7,74	8,64
	(9,33)	(6,95)	(-0,25)	(6,63)	(0,33)	(0,36)
R&D intensity 2	-0,07	-0,07	-0,08	-0,11	-0,07	-0,11
	(-0,73)	(-0,76)	(-0,88)	(-1,20)	(-0,74)	(-1,15)
Asset tangibility			0,04	-0,03		-0,02
			(0,58)	(-0,51)		(-0,37)
Leverage		0,01			0,01	-0,02
		(0,10)			(0,14)	(-0,06)
Log_Age		-4,03 ***		-4,30 ***	-4,05 ***	-4,31 ***
		(-3,68)		(-3,85)	(-3,70)	(-3,83)
Log_Size			1,42		1,15	1,44
			(0,99)		(0,82)	(1,01)
Industry_control			-4,19 *	-4,60 *		-4,91 **
			(-1,76)	(-1,95)		(-2,05)
Adjusted R2	0,0%	0,9%	0,0%	1,1%	0,9%	1,1%

Profit margin						
Model	1	2	3	4	5	6
Constant	7,88 ***	20,14 ***	-134,26 ***	3,04	-111,85 ***	-121,05 ***
	(7,49)	(7,95)	(-8,89)	(0,94)	(-7,58)	(-8,10)
R&D intensity 2	-0,73 ***	-0,70 ***	-0,60 ***	-0,65 ***	-0,67 ***	-0,58 ***
	(-12,2)	(-11,94)	(-9,97)	(-10,51)	(-11,70)	(-9,74)
Asset tangibility			0,10 **	0,02		0,12 ***
			(2,35)	(0,58)		(2,80)
Leverage		-0,40 ***			-0,38 ***	-0,37 ***
		(-8,05)			(-7,79)	(-7,63)
Log_Age		-2,77 ***		-1,47 **	-3,09 ***	-2,42 ***
		(-3,88)		(-2,01)	(-4,46)	(-3,44)
Log_Size			7,90 ***		7,93 ***	7,82 ***
			(8,82)		(9,07)	(8,91)
Industry_control			8,83 ***	9,86 ***		7,41 ***
			(5,71)	(6,22)		(4,86)
Adjusted R2	9,6%	13,9%	16,7%	12,3%	18,7%	20,3%

Non-high-tech sample

	ROA							ROE					
Model	1	2	3	4	5	6	Model	1	2	3	4	5	6
Constant	8,84 ***	19,43 ***	-64,44 ***	16,37 ***	-54,32 ***	-53,85 ***	Constant	11,72 ***	34,58 ***	-116,66 ***	27,47 ***	-94,18 ***	-93,91 ***
	(21,03)	(17,56)	(-9,25)	(13,47)	(-7,90)	(-7,80)		(13,04)	(14,62)	(-7,80)	(10,58)	(-6,38)	(-6,33)
R&D intensity 2	-0,23 ***	-0,25 ***	-0,18 ***	-0,22 ***	-0,22 ***	-0,20 ***	R&D intensity 2	-0,35 ***	-0,37 ***	-0,24 ***	-0,32 ***	-0,32 ***	-0,27 ***
	(-10,27)	(-10,97)	(-7,80)	(-9,57)	(-9,81)	(-8,52)		(-7,11)	(-7,76)	(-4,80)	(-6,43)	(-6,77)	(-5,46)
Asset tangibility			0,04	-0,03 **		0,01	Asset tangibility			0,03	-0,04		0,05
			(0,25)	(-1,98)		(0,81)				(0,86)	(-1,17)		(1,45)
Leverage		-0,16 ***			-0,14 ***	-0,15 ***	Leverage		-0,33 ***			-0,29 ***	-0,32 ***
		(-7,87)			(-6,91)	(-7,16)			(-7,62)			(-6,81)	(-7,25)
Log_Age		-2,81 ***		-2,62 ***	-3,04 ***	-2,87 ***	Log_Age		-6,12 ***		-5,63 ***	-6,51 ***	-6,06 ***
		(-8,92)		(-8,11)	(-9,77)	(-9,06)			(-9,08)		(-8,15)	(-9,74)	(-8,92)
Log_Size			4,29 ***		4,42 ***	4,29 ***	Log_Size			7,46 ***		7,71 ***	7,45 ***
			(10,37)		(10,87)	(10,51)				(8,40)		(8,83)	(8,49)
Industry_control			2,26 ***	2,77 ***		1,80 ***	Industry_control			4,86 ***	5,64 ***		3,88 ***
			(3,43)	(4,20)		(2,78)				(3,44)	(4,01)		(2,79)
Adjusted R2	2,9%	6,4%	6,3%	5,2%	9,4%	9,7%	Adjusted R2	1,4%	4,9%	3,9%	3,8%	7,0%	7,3%
	Revenue growth							**Profit margin**					
Model	1	2	3	4	5	6	Model	1	2	3	4	5	6
Constant	12,62 ***	27,11 ***	-27,79 **	26,79 ***	-18,91	-19,64	Constant	6,31 ***	17,78 ***	-68,31 ***	14,65 ***	-55,24 ***	-55,96 ***
	(16,16)	(12,87)	(-2,02)	(11,64)	(-1,39)	(-1,44)		(12,75)	(13,64)	(-8,28)	(10,20)	(-6,78)	(-6,83)
R&D intensity 2	0,02	0,01	0,06	0,02	0,02	0,03	R&D intensity 2	-0,28 ***	-0,29 ***	-0,24 ***	-0,28 ***	-0,26 ***	-0,25 ***
	(-0,53)	(0,03)	(1,47)	(0,40)	(0,46)	(0,63)		(-10,46)	(-11,09)	(-8,54)	(-10,11)	(-10,08)	(-9,16)
Asset tangibility			0,09 ***	0,04		0,02	Asset tangibility			0,02	-0,02		0,03
			(2,60)	(1,17)		(0,73)				(0,78)	(-1,16)		(1,61)
Leverage		0,10 ***			0,11 ***	0,11 ***	Leverage		-0,20 ***			-0,18 ***	-0,19 ***
		(2,69)			(2,96)	(2,65)			(-8,25)			(-7,42)	(-7,70)
Log_Age		-4,94 ***		-4,83 ***	-5,02 ***	-4,90 ***	Log_Age		-2,96 ***		-2,77 ***	-3,18 ***	-3,02 ***
		(-8,23)		(-7,89)	(-8,37)	(-8,04)			(-7,97)		(-7,26)	(-8,64)	(-8,06)
Log_Size			2,28 ***		2,74 ***	2,73 ***	Log_Size			4,39 ***		4,37 ***	4,34 ***
			(2,80)		(3,42)	(3,39)				(8,96)		(9,08)	(8,95)
Industry_control			0,71	0,65		0,22	Industry_control			1,17	1,68 **		0,66
			(0,57)	(0,52)		(0,18)				(1,50)	(2,16)		(0,86)
Adjusted R2	0,0%	2,2%	0,4%	2,1%	2,6%	2,5%	Adjusted R2	3,0%	6,2%	5,3%	4,5%	8,4%	8,5%

Appendix 6: Robustness outcomes with 2-year lag

High-tech sample

Model	Lagged ROA 1	2	3	4	5	6
Constant	6,56 ***	7,84 ***	8,57	9,21 ***	9,27	9,41
	(9,39)	(3,98)	(0,66)	(3,60)	(0,74)	(0,72)
R&D intensity	-0,23 ***	-0,23 ***	-0,23 ***	-0,23 ***	-0,23 ***	-0,24 ***
	(-7,48)	(-7,46)	(-6,93)	(-7,04)	(-7,39)	(-6,96)
Asset tangibility			0,02	0,01		0,01
			(0,56)	(0,34)		(0,17)
Leverage		0,04			0,04	0,04
		(0,98)			(0,98)	(0,90)
Log_Age		-0,53		-0,61	-0,53	-0,53
		(-0,92)		(-1,05)	(-0,90)	(-0,89)
Log_Size			-0,09		-0,09	-0,04
			(-0,11)		(-0,12)	(-0,05)
Industry_control			-1,01	-1,11		-1,11
			(-0,77)	(-0,84)		(-0,84)
Adjusted R2	5,0%	5,0%	4,8%	4,9%	4,9%	4,8%

Model	Lagged ROE 1	2	3	4	5	6
Constant	4,72 ***	7,21 *	16,80	7,15	23,02	17,86
	(3,29)	(1,78)	(0,63)	(1,36)	(0,89)	(0,67)
R&D intensity	-0,33 ***	-0,32 ***	-0,34 ***	-0,34 ***	-0,32 ***	-0,33 ***
	(-5,20)	(-4,93)	(-4,93)	(-4,93)	(-4,97)	(-4,61)
Asset tangibility			0,08	0,08		0,08
			(1,11)	(1,11)		(1,15)
Leverage		-0,05			-0,05	-0,07
		(-0,52)			(-0,53)	(-0,77)
Log_Age		-0,71		-0,34	-0,63	-0,46
		(-0,59)		(-0,29)	(-0,53)	(-0,38)
Log_Size			-0,64		-0,96	-0,60
			(-0,41)		(-0,62)	(-0,38)
Industry_control			-3,05	-3,11		-3,09
			(-1,13)	(-1,15)		(-1,14)
Adjusted R2	2,4%	2,3%	2,5%	2,5%	2,2%	2,4%

Model	Lagged Revenue growth 1	2	3	4	5	6
Constant	9,12 ***	12,15 ***	142,69 ***	18,55 ***	137,66 ***	143,87 ***
	(7,33)	(3,46)	(6,31)	(4,09)	(6,23)	(6,34)
R&D intensity	0,08	0,07	-0,03	0,03	0,03	-0,03
	(1,40)	(1,34)	(-0,48)	(0,46)	(0,49)	(-0,53)
Asset tangibility			-0,02	0,03		-0,03
			(-0,27)	(0,44)		(-0,44)
Leverage		0,03			0,02	0,02
		(0,33)			(0,26)	(0,24)
Log_Age		-1,07		-1,13	-0,48	-0,68
		(-1,04)		(-1,09)	(-0,47)	(-0,66)
Log_Size			-7,59 ***		-7,61 ***	-7,53 ***
			(-5,71)		(-5,75)	(-5,64)
Industry_control			-6,85 ***	-7,13 ***		-6,96 ***
			(-2,98)	(-3,05)		(-3,02)
Adjusted R2	0,1%	0,0%	3,8%	0,9%	3,0%	3,7%

Model	Lagged Profit margin 1	2	3	4	5	6
Constant	7,94 ***	10,09 ***	-28,48	11,16 ***	-27,4	-26,96
	(8,02)	(3,61)	(-1,56)	(3,08)	(-1,54)	(-1,47)
R&D intensity	-0,46 ***	-0,45 ***	-0,47 ***	-0,48 ***	-0,43 ***	-0,45 ***
	(-10,74)	(-10,13)	(-9,80)	(-10,29)	(-9,71)	(-9,17)
Asset tangibility			0,04	-0,02		0,01
			(0,01)	(-0,43)		(0,18)
Leverage		-0,10			-0,09	-0,10
		(-1,58)			(-1,55)	(-1,60)
Log_Age		-0,46		-0,32	-0,64	-0,65
		(-0,57)		(-0,38)	(-0,78)	(-0,78)
Log_Size			2,29 **		2,27 **	2,35 **
			(2,12)		(2,13)	(2,18)
Industry_control			-2,02	-2,04		-2,09
			(-1,09)	(-1,09)		(-1,12)
Adjusted R2	9,9%	9,9%	10,1%	9,7%	10,2%	10,2%

Non-high-tech sample

Lagged ROA

Model	1	2	3	4	5	6
Constant	8,31 ***	13,66 ***	-16,58 **	11,29 ***	-12,83	-14,31 *
	(18,55)	(11,69)	(-2,06)	(8,90)	(-1,61)	(-1,78)
R&D intensity	-0,25 ***	-0,25 ***	-0,21 ***	-0,23 ***	-0,23 ***	-0,21 ***
	(-10,31)	(-10,28)	(-8,26)	(-9,13)	(-9,51)	(-8,23)
Asset tangibility			0,01	-0,05		0,02
			(0,61)	(-0,26)		(0,86)
Leverage		-0,06 ***			-0,05 ***	-0,06 ***
		(-2,89)			(-2,54)	(-2,90)
Log_Age		-1,51 ***		-1,29 ***	-1,67 ***	-1,48 ***
		(-4,48)		(-3,78)	(-4,94)	(-4,31)
Log_Size			1,41 ***		1,61 ***	1,59 ***
			(2,94)		(3,35)	(3,30)
Industry_control			2,42 ***	2,35 ***		2,06 ***
			(3,28)	(3,20)		(2,80)
Adjusted R2	4,0%	4,9%	4,8%	5,0%	5,3%	5,7%

Lagged ROE

Model	1	2	3	4	5	6
Constant	10,97 ***	24,62 ***	-8,76	20,49 ***	-1,23	-4,25
	(11,52)	(9,93)	(-0,51)	(7,61)	(-0,07)	(-0,25)
R&D intensity	-0,40 ***	-0,40 ***	-0,35 ***	-0,37 ***	-0,38 ***	-0,34 ***
	(-7,78)	(-7,75)	(-6,36)	(-6,90)	(-7,34)	(-6,36)
Asset tangibility			0,03	0,04		0,04
			(0,84)	(0,09)		(0,95)
Leverage		-0,11 ***			-0,11 ***	-0,12 ***
		(-2,58)			(-2,41)	(-2,73)
Log_Age		-4,00 ***		-3,62 ***	-4,16 ***	-3,84 ***
		(-5,60)		(-5,00)	(-5,77)	(-5,25)
Log_Size			1,03		1,57	1,58
			(1,01)		(1,54)	(1,53)
Industry_control			3,86 **	3,38 **		2,99 *
			(2,46)	(2,16)		(1,91)
Adjusted R2	2,3%	3,6%	2,6%	3,5%	3,7%	3,9%

Lagged Revenue growth

Model	1	2	3	4	5	6
Constant	10,30 ***	15,05 ***	165,26 ***	12,69 ***	167,88 ***	164,76 ***
	(12,49)	(6,98)	(11,41)	(5,43)	(11,62)	(11,31)
R&D intensity	0,05	0,04	-0,01	0,08	-0,04	-0,01
	(1,03)	(1,01)	(-0,21)	(1,71)	(-0,97)	(-0,24)
Asset tangibility			0,05	0,09 ***		0,04
			(1,49)	(2,62)		(1,27)
Leverage		0,07 *			0,03	0,01
		(1,85)			(0,80)	(0,32)
Log_Age		-1,81 ***		-1,51 **	-0,84	-0,57
		(-2,92)		(-2,40)	(-1,37)	(-0,91)
Log_Size			-9,40 ***		-9,30 ***	-9,27 ***
			(-10,90)		(-10,69)	(-10,61)
Industry_control			2,14	0,95		2,05
			(1,61)	(0,70)		(1,54)
Adjusted R2	0,0%	0,4%	4,9%	0,7%	4,7%	4,9%

Lagged Profit margin

Model	1	2	3	4	5	6
Constant	7,12 ***	13,78 ***	-25,43 **	11,23 ***	-19,25 *	-21,27 **
	(12,61)	(9,37)	(-2,50)	(7,01)	(-1,91)	(-2,10)
R&D intensity	-0,27 ***	-0,27 ***	-0,23 ***	-0,26 ***	-0,25 ***	-0,23 ***
	(-8,81)	(-8,76)	(-7,22)	(-8,08)	(-8,01)	(-7,14)
Asset tangibility			0,01	-0,01		0,03
			(0,63)	(-0,23)		(1,21)
Leverage		-0,11 ***			-0,10 ***	-0,11 ***
		(-4,23)			(-3,88)	(-4,17)
Log_Age		-1,74 ***		-1,53 ***	-1,95 ***	-1,79 ***
		(-4,11)		(-3,55)	(-4,57)	(-4,13)
Log_Size			1,89 ***		2,01 ***	2,04 ***
			(3,12)		(3,32)	(3,36)
Industry_control			1,59 *	1,53 *		1,10
			(1,71)	(1,65)		(1,19)
Adjusted R2	2,9%	4,1%	3,4%	3,5%	4,5%	4,6%

Appendix 7: Quantile regressions

High-tech sample

ROA

Quantile	Q1	Q2	Q3	Q4	Q5	Q7	Q8	Q9
Constant	-118,30 ***	-58,80 ***	-36,15 ***	-21,25 *	-14,17	-14,27	-20,95 *	-15,15
	(-4.93)	(-3,81)	(-3,13)	(-1,83)	(-1,60)	(-1,24)	(-1,73)	(-0,99)
R&D intensity	-0,63 ***	-0,64 ***	-0,57 ***	-0,42 ***	-0,36 ***	-0,33 ***	-0,32 ***	-0,31 ***
	(-10,47)	(-16,58)	(-19.80)	(-14,27)	(-16,16)	(-11,53)	(-10,40)	(-7,91)
Asset tangibility	0,06	0,40	0,01	0,01	-0,02	-0,06 **	-0,10 ***	0,15 ***
	(0,92)	(1,00)	(0.41)	(0,31)	(-0,74)	(-2,16)	(-3,06)	(-3,82)
Leverage	-0,03	-0,10 **	-0,04	-0,06 *	-0,08 ***	-0,15 ***	-0,14 ***	-0,18 ***
	(-0,35)	(-2,01)	(-1.21)	(-1,68)	(-2,82)	(-4,12)	(-3,73)	(-3,69)
Log_Age	-2,44 **	-2,07 ***	-1,29 **	-1,62 ***	-1,34 ***	-1,77 ***	-1,49 ***	-1,69 **
	(-2,22)	(-2,92)	(-2.44)	(-3,04)	(-3,30)	(-3,35)	(-2,69)	(-2,40)
Log_Size	7,22 ***	4,16 ***	2,85 ***	2,06 ***	1,73 ***	2,20 ***	2,78 ***	2,96 ***
	(5,11)	(4,57)	(4.20)	(3,01)	(3,30)	(3,25)	(3,90)	(3,27)
Industry_control	-2,28	-2,87 *	-2,68 **	-1,32	-0,97	-0,57	-0,47	-2,47
	(-0,95)	(-1,86)	(-2,32)	(-1,13)	(-1.10)	(-0,49)	(-0,38)	(-1,61)
Pseudo R2	19,5%	17,5%	15,7%	13,2%	11,6%	10,2%	10,1%	9,9%

ROE

Quantile	Q1	Q2	Q3	Q4	Q5	Q7	Q8	Q9
Constant	-296,34 ***	-170,02 ***	-55,16 **	-13,51	4,03	7,46	-0,41	48,40
	(-4,09)	(-3,91)	(-2,11)	(-0,66)	(0,26)	(0,54)	(-0,02)	(1,19)
R&D intensity	-0,75 ***	-0,94 ***	-0,82 ***	-0,72 ***	-0,54 ***	-0,52 ***	-0,48 ***	-0,48 ***
	(-4,14)	(-8,55)	(-12,54)	(-14,01)	(-13,72)	(-15,00)	(-10,82)	(-4,71)
Asset tangibility	0,08	0,01	0,03	0,00	-0,02	-0,05	-0,08 *	-0,22 **
	(0,40)	(0,07)	(0,44)	(0,06)	(-0,60)	(-1,34)	(-1,66)	(-2,08)
Leverage	-1,30 ***	-0,62 ***	-0,61 ***	-0,26 ***	-0,21 ***	-0,18 ***	-0,06 *	0,12
	(-5,58)	(-4,47)	(-7,31)	(-3,92)	(-4,23)	(-3,99)	(-1,66)	(0,92)
Log_Age	-1,41	-1,97	-1,47	-2,25 **	-2,27 ***	-2,54 ***	-2,19 ***	-4,45 **
	(-0,42)	(-0,99)	(-1,23)	(-2,39)	(-3,19)	(-4,01)	(-2,70)	(-2,39)
Log_Size	17,21 ***	10,97 ***	4,36 ***	2,10 *	1,12	1,43 *	2,11 **	0,25
	(4,03)	(4,28)	(2,83)	(1,73)	(1,23)	(1,76)	(2,02)	(0,10)
Industry_control	-8,19	-7,84 *	-3,85	-2,00	-0,96	-0,79	-1,03	-1,11
	(-1,13)	(-1.80)	(-1,47)	(-0,97)	(-0,62)	(-0,57)	(-0,58)	(-0,27)
Pseudo R2	13,3%	12,8%	11,8%	9,9%	8,5%	6,7%	5,5%	4,2%

Revenue growth

Quantile	Q1	Q2	Q3	Q4	Q5	Q7	Q8	Q9
Constant	-128,13 ***	-0,63 **	-45,53 **	-5,14	17,13	62,09 **	156,57 ***	273,55 ***
	(-4,12)	(-2,52)	(-2,26)	(-0,24)	(0,82)	(2,21)	(3,10)	(3,46)
R&D intensity	-0,27 ***	-0,34 ***	-0,33 ***	-0,24 ***	-0,19 ***	-0,12 *	0,08	0,39 **
	(-3,60)	(-5,56)	(-6,83)	(-4,73)	(-3,72)	(-1,77)	(0,62)	(2,02)
Asset tangibility	-0,15 *	-0,04	-0,07	-0,09 *	-0,10 *	-0,12 *	-0,22 *	-0,23
	(-1,90)	(-0,65)	-(1,50)	(-1,76)	(-1,87)	(-1,72)	(-1,74)	(-1,18)
Leverage	0,11	0,12	0,07	0,04	0,01	0,01	-0,09	-0,02
	(1,17)	(1,49)	(1,07)	(0,57)	(0,11)	(0,16)	(-0,60)	(-0,09)
Log_Age	-2,01	-1,66	-1,04	-3,05 ***	-3,05 ***	-4,26 ***	-6,42 ***	-8,25 **
	(-1,44)	(-1,47)	(-1,15)	(-3,23)	(-3,26)	(-3,38)	(-2,83)	(-2,32)
Log_Size	7,43 ***	3,95 ***	3,18 ***	1,44	0,34	-1,41	-5,87 **	-11,10 **
	(4,07)	(2,68)	(2,69)	(1,16)	(0,28)	(-0,85)	(-1,98)	(-2,39)
Industry_control	-8,91 ***	-6,15 **	-4,70 **	-4,41 **	-2,87	-3,82	-6,10	-16,32 **
	(-2,99)	(-2,56)	(-2,44)	(-2,19)	(-1,44)	(-1,42)	(-1,26)	(-2,16)
Pseudo R2	4,8%	3,5%	2,3%	1,3%	0,8%	0,8%	1,5%	4,8%

Profit margin

Quantile	Q1	Q2	Q3	Q4	Q5	Q7	Q8	Q9
Constant	-209,41 ***	-135,82 ***	-72,72 ***	-19,78	-3,17	11,50	9,65	23,49
	(-8,06)	(-5,43)	(-3,88)	(-1,34)	(-0,27)	(0,89)	(0,50)	(1,17)
R&D intensity	-1,17 ***	-1,01 ***	-0,96 ***	-0,93 ***	-0,83 ***	-0,68 ***	-0,52 ***	-0,51 ***
	(-17,83)	(-16,07)	(-20,28)	(-24,92)	-(27,55)	(-20,92)	(-10,74)	(-10,21)
Asset tangibility	-0,01	-0,06	-0,04	-0,05	-0,07 **	-0,07 **	-0,07	-0,20 ***
	(-0,02)	(-0,93)	(-0,81)	(-1,31)	(-2,20)	(-1,99)	(-1,49)	(-3,89)
Leverage	-0,19 **	-0,18 **	-0,2 ***	-0,16 ***	-0,16 ***	-0,25 ***	-0,33 ***	-0,36 ***
	(-2,26)	(-2,22)	(-2,65)	(-3,37)	(-4,12)	(-6,06)	(-5,38)	(-5,58)
Log_Age	-2,81 **	-2,47 **	-1,45 *	-1,20 *	-0,94 *	-1,59 ***	-1,60 *	-1,41
	(-2,36)	(-2,15)	-(1,69)	(-1,78)	(-1,72)	(-2,68)	(-1,81)	(-1,54)
Log_Size	12,85 ***	8,98 ***	5,21 ***	2,34 ***	1,43 ***	1,11	1,46	1,69
	(8,40)	(6,09)	(4,72)	(2,69)	(2,03)	(1,46)	(1,29)	(1,44)
Industry_control	-2,93	-3,05	-0,60	-2,01	-1,26	-3,06 **	-3,81 **	-12,49 ***
	(-1,13)	(-1,22)	(-0,32)	(-1,36)	(-1,06)	(-2,36)	(-1,98)	(-6,24)
Pseudo R2	36,0%	29,4%	24,6%	19,9%	15,8%	10,2%	8,1%	9,2%

Non-high-tech sample

ROA

Quantile	Q1	Q2	Q3	Q4	Q5	Q7	Q8	Q9
Constant	-20,72	-20,95 **	-21,97 ***	-23,24 ***	-25,42 ***	-24,13 ***	-18,05 *	-32,02 ***
	(-1,06)	(-2,01)	(-2,96)	(-3,73)	(-4,68)	(-3,67)	(-1,88)	(-2,77)
R&D intensity	-0,69 ***	-0,64 ***	-0,43 ***	-0,29 ***	-0,23 ***	-0,15 ***	-0,17 ***	-0,18 ***
	(-12,02)	(-20,83)	(-19,42)	(-15,69)	(-14,37)	(-7,95)	(-5,86)	(-5,41)
Asset tangibility	0,07	0,02	0,01	0,00	0,00	-0,04 ***	-0,08 ***	-0,12 ***
	(1,60)	(0,68)	(0,55)	(0,12)	(-0,21)	(-2,88)	(-3,56)	(-4,78)
Leverage	-0,12 **	-0,06 **	-0,07 ***	-0,06 ***	-0,07 ***	-0,11 ***	-0,14 ***	-0,17 ***
	(-2,18)	(-2,12)	(-3,30)	(-3,77)	(-4,96)	(-5,92)	(-5,37)	(-5,53)
Log_Age	-3,68 ***	-3,26 ***	-2,56 ***	-2,04 ***	-2,20 ***	-2,53 ***	-2,77 ***	-3,65 ***
	(-4,54)	(-7,52)	(-8,27)	(-7,89)	(-9,75)	(-9,23)	(-6,94)	(-7,61)
Log_Size	1,73	2,18 ***	2,20 ***	2,24 ***	2,52 ***	2,80 ***	2,78 ***	4,24 ***
	(1,49)	(3,51)	(4,95)	(6,03)	(7,78)	(7,12)	(4,86)	(6,15)
Industry_control	0,98	-1,06	-0,52	-0,32	-0,56	-0,01	0,40	0,67
	(0,57)	(-1,15)	(-0,79)	(-0,57)	(-1,.17)	(-0,02)	(0,47)	(0,65)
Pseudo R2	12,3%	10,5%	7,7%	6,1%	5,5%	5,5%	6,1%	7,9%

ROE

Quantile	Q1	Q2	Q3	Q4	Q5	Q7	Q8	Q9
Constant	-4,02	-2,24	-20,99	-28,90 ***	-31,17 ***	-35,45 ***	-52,00 ***	-68,07 ***
	(-0,08)	(-0,09)	(-1,52)	(-2,67)	(-3,08)	(-2,97)	(-3,34)	(-2,60)
R&D intensity	-1,45 ***	-1,08 ***	-0,77 ***	-0,52 ***	-0,32 ***	-0,23 ***	-0,25 ***	-0,22 ***
	(-10,19)	(-14,36)	(-18,94)	(-16,20)	(-10,87)	(-6,44)	(-5,48)	(-2,90)
Asset tangibility	0,27 **	0,05	0,04	0,03	0,00	-0,14 ***	-0,23 ***	0,37 ***
	(2,51)	(0,91)	(1,15)	(1,12)	(-0,13)	(-5,23)	(-6,52)	(-6,29)
Leverage	-1,06 ***	-0,53 ***	-0,23 ***	-0,13 ***	-0,09 ***	0,05	0,16 ***	0,24 ***
	(-8,12)	(-7,69)	(-6,19)	(-4,27)	(-3,26)	(1,58)	(3,67)	(3,44)
Log_Age	-0,74 ***	-5,60 ***	-4,82 ***	-3,92 ***	-4,26 ***	-5,43 ***	-7,05 ***	-10,19 ***
	(-3,66)	(-5,26)	(-8,41)	(-8,71)	(-10,12)	(-10,93)	(-10,87)	(-9,35)
Log_Size	1,31	1,80	2,86 ***	3,20 ***	3,51 ***	4,47 ***	6,23 ***	8,54 ***
	(0,45)	(1,18)	(3,48)	(4,95)	(5,81)	(6,27)	(6,70)	(5,46)
Industry_control	0,58	-0,59	-1,15	-0,57	-0,62	0,81	1,39	1,65
	(0,13)	(-0,26)	(-0,94)	(-0,59)	(-0,69)	(0,77)	(1,00)	(0,71)
Pseudo R2	12,6%	9,9%	6,8%	4,8%	3,8%	4,0%	5,2%	6,7%

Revenue growth

Quantile	Q1	Q2	Q3	Q4	Q5	Q7	Q8	Q9
Constant	-204,08 ***	-107,46 ***	-61,80 ***	-30,46 **	-6,10	60,90 ***	115,12 ***	155,43 ***
	(-8,98)	(-6,62)	(-4,40)	(-2,54)	(-0,48)	(3,60)	(4,12)	(3,70)
R&D intensity	-0,01	-0,06	-0,06	-0,07 **	-0,07 **	-0,11 **	-0,11	-0,15
	(-0,09)	(-1,31)	(-1,57)	(-2,21)	(-2,07)	(-2,34)	(-1,42)	(-1,29)
Asset tangibility	0,07	0,02	0,02	0,03	0,01	-0,03	-0,08	-0,14
	(1,32)	(0,67)	(0,66)	(1,31)	(0,20)	(-0,87)	(-1,30)	(-1,53)
Leverage	0,20 ***	0,13 ***	0,14 ***	0,11 ***	0,12 ***	0,14 ***	0,16 **	0,12
	(3,42)	(3,03)	(3,93)	(3,47)	(3,47)	(3,13)	(2,14)	(1,08)
Log_Age	1,05	-0,21	-1,24 **	-0,96 **	-1,60 ***	-3,24 ***	-6,16 ***	12,09 ***
	(1,14)	(-0,31)	(-2,19)	(-1,99)	(-3,09)	(-4,74)	(-5,45)	(-7,13)
Log_Size	10,75 ***	5,90 ***	3,75 ***	2,12 ***	1,08	-1,89 *	-3,93 **	-3,99
	(7,95)	(6,11)	(4,49)	(2,98)	(1,41)	(-1,88)	(-2,36)	(-1,60)
Industry_control	-7,88 ***	-5,42 ***	-3,95 ***	-2,88 ***	-0,93	0,11	-0,05	4,47
	(-4,06)	(-3,90)	(-3,29)	(-2,80)	(-0,85)	(0,08)	(-0,02)	(1,25)
Pseudo R2	4,5%	2,0%	1,1%	0,7%	0,6%	1,1%	1,8%	4,2%

Quantile regressions

Quantile	Q1	Q2	Q3	Q4	Q5	Q7	Q8	Q9
Constant	-101,31 ***	42,29 ***	-21,56 **	-17,28 **	-22,74 ***	-4,95	9,67	50,60 ***
	(-3,89)	(-2,66)	(-2,13)	(-2,20)	(-3,36)	(-0,60)	(0,93)	(2,98)
R&D intensity	-1,24 ***	-0,97 ***	-0,70 ***	-0,42 ***	-0,20 ***	-0,12 ***	-0,13 ***	-0,16 ***
	(-16,13)	(-20,67)	(-23,52)	(-17,99)	(-10,08)	(-5,09)	(-4,11)	(-3,28)
Asset tangibility	0,10 *	0,03	0,01	0,01	0,01	-0,05 **	-0,09 ***	-0,19 ***
	(1,66)	(0,96)	(0,33)	(0,71)	(0,47)	(-2,55)	(-3,75)	(-5,00)
Leverage	-0,22 ***	-0,16 ***	-0,12 ***	-0,12 ***	-0,10 ***	-0,16 ***	-0,18 ***	-0,22 ***
	(-3,18)	(-3,83)	(-4,42)	(-5,71)	(-5,59)	(-7,21)	(-6,53)	(-4,77)
Log_Age	-4,98 ***	-3,57 ***	-2,67 ***	-2,17 ***	-1,85 ***	-1,54 ***	-1,98 ***	-2,44 ***
	(-4,59)	(-5,40)	(-6,35)	(-6,64)	(-6,56)	(-4,49)	(-4,57)	(-3,45)
Log_Size	6,85 ***	3,58 ***	2,29 ***	1,94 ***	2,21 ***	1,50 ***	1,04 *	-0,67
	(4,40)	(3,78)	(3,79)	(4,12)	(5,46)	(3,06)	(1,67)	(-0,66)
Industry_control	1,57	-0,04	0,63	0,53	0,57	0,41	0,12	-0,57
	(0,68)	(-0,03)	(0,70)	(0,76)	(0,94)	(0,56)	(0,13)	(-0,38)
Pseudo R2	18,8%	13,8%	8,7%	4,9%	3,2%	3,0%	3,6%	4,9%

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