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The Impact of Green Innovation on Firm Financial Performance

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ABSTRACT

This study investigates the relationship between green innovation and firm performance. The hypothesis that goes with this is: “green innovation affects firm financial performance positively”. To substantiate this hypothesis the study uses an unbalanced panel dataset and a sample consisting of 450 unique firms with at least one European granted green patent in one of the total 1,314 firm year observations between the years 2007 and 2014. These firms have a combined number of 7,700 new European green patents granted by EPO with its 9,087 citations. In the OLS regression analysis for the full sample, both the number of patents and citations, proxies for green innovation, are positively related to ROE as the firm performance measure. For the number of citations this relationship is also statistically significant at the 1% level. However, looking at ROA as the performance measure, the number of citations still shows a positive and significant sign, but for the number of patents it becomes negative and even significant at the 5% level for some models. For ROS and Profit Margin as the performance measures the regression reports extremely weak results and almost no significance at all for both proxies of green innovation. With these mixed results the hypothesis only receives partial support.

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1 INTRODUCTION

The world is changing and it is changing tremendously fast. The consequences of global warming are affecting the world. For the last 45 years, the earth's average temperature rose 0.17°C per decade. That is double the 0.07°C per decade increase that occurred during the entire period of recorded observations between 1880 and 2015 (Dahlman, 2017). On the other side of the timeline, looking into the future, it can be seen that the sea levels will rise by 18 to almost 60 centimeter by the end of this century (IPCC, 2007). The latter is a result of the strong decrease of 7% of the sea ice in the Arctic Ocean since 1979 (Soyez & Grassl, 2008). These facts and many others indicate that the world and in particular firms need to deal with the consequences of the changing environment. For firms, in order to change their way of operating and be sustainable for the future, one of the most logical ways to do this is by investing in green innovation.

The world became aware of the environmental problems after 1972 when there was a United Nations conference on the human environment (Dangelico, 2016). However, two decades ago the world was still dealing with firms that were inexperienced in environmental solutions. Also, customers did not know that resource inefficiency meant that they had to pay for the cost of pollution (Porter & van der Linde, 1995). Schiederig, Tietze and Herstatt (2012) show that one possible reason could be that until 1990 there was hardly any research about green innovation. In the seven years thereafter the field of study became more popular with using environmental innovation as the main term. Since 2000, the term sustainable innovation became more popular and from 2005 until now the concepts of green and eco innovation were used increasingly. The different terms of describing green innovation are of interchangeable usage. This study follows the definition of green innovation introduced by Schiederig et al. (2012), namely: "The innovation object may be a product, process, service or method and it should satisfy a user's need or solve a problem and therefore be competitive on the market. Regarding the environmental aspect it should reduce negative impact, and a full life cycle analysis and a thorough analysis of all input- and output factors must be done with the aim of a reduction of resource consumption and with an economical or ecological intention. This all is for setting a new innovation/green standard to the firm".

Corporate environmental management was already of real importance two decades ago (Russo & Fouts, 1997). The rise of strict international regulation and conventions of environmental protection was because of the fact of growing attention towards the environment nowadays, which led to a change of the strategies and industries. Chen, Lai and Wen (2006) add to this that in general many businesses have had a negative view of green innovation with the thought that investing in the protection of the environment would be harmful to their businesses. However, the study concluded that environmental pressure is something all businesses have to deal with these days and this asks for a professional attitude towards managing it. Businesses do not have to avoid these pressures, because by carrying out green innovation they could be turned into unique competitive advantages. Global competition demands environmental innovations to raise resource productivity (Porter & van der Linde, 1995). Next to that, proactive strategies in green innovation also prevent firms from facing environmental protests or penalties and it helps them developing new market opportunities. So, overall, green innovation improves the performance of a firm.

The field of innovation is already widely studied[1]. However, the green part of innovation is still quite a new subject of research. Although, some studies already investigated green innovation, almost all of them used a survey to gather their data. Performing a survey could bring disadvantages like data error due to non-responses or questions could be interpreted differently by different respondents. The study of Aguilera-Caracuel and Ortiz-de-Mandojana (2013) is the only study of green innovation that does not use a survey to gather their data. This study will use the same patent database and Y02 classification for green patents they use. However, the Y02 classification has been available for public as part of the classification scheme since 2010 and therefore during the time of research of their study there were not many green patents yet[2]. Next to that, it is difficult to measure all four parts of green innovation[3] with using a survey and that is why almost all green innovation studies only focus on green product innovation. By using patent data, like this study, it is able to not only use green product innovation, but also include the other parts. So, the intention of this paper is to investigate the impact of green innovation on firm performance while using an unbalanced panel dataset and to provide concrete suggestions for the field of study. Therefore, this study contributes to the literature of innovation by going deeper into the green part of it, by adding new empirical evidence to green innovation based on the use of panel data instead of survey data, and by not making a distinction between the four parts of innovation and thus not focusing on green product innovation alone. Formulated into a research question: “To what extent does green

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[1] Supporting literature: Griliches et al., 1986; Hall et al., 1986; DeCarolis & Deeds, 1999; Hall et al., 2001; Melvin, 2002; Feeny & Rogers, 2003; Hall et al., 2005; Frietsch & Grupp, 2006; Arora et al., 2008; Harhoff & Wagner, 2009; Artz et al., 2010; Czarnitzki & Kraft, 2012; Choi & Williams, 2013; Santos et al., 2014; Seru, 2014; Chen et al., 2018; Huang & Hou, 2019; Zhou & Sadeghi, 2019.

[2] EPO. “Y02 – E-learning module”. e-courses.epo.org
https://e-courses.epo.org/wbts/y02/index.html (accessed April 24, 2020)

[3] These four parts are green product, process, service, and method innovation.

innovation influence firm financial performance?”. With using a sample only consisting of firms with at least one granted green patent an answer will be given to this question. The patent data is gathered from the EPO database for the period of 2007-2014 and the financial data is gathered from the ORBIS database for the period of 2010-2017. The full sample consists of a total of 450 unique firms with 1,314 firm year observations and with a total of 7,700 newly granted green patents and 9,087 citations. An OLS regression analysis with an unbalanced panel dataset is performed to test the hypothesis. Additively, robustness checks will be performed to examine if the results of the main analysis are consistent, robust and provide reliable outcomes.

The first chapter of this study concerns an introduction to green innovation, a literature review on theories and empirical evidence within this field of study, and with this a hypothesis will be formed. Thereafter, a methodology will be substantiated wherein the scope of research methods and variables will be explained. The next chapter described the data collection method and the final full sample used in this study. After this, the results of the main analysis and robustness checks will be reported with a thorough substantiation. Lastly, a conclusion will be made and limitations of this study and avenues for further research will be given.

2 LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

2.1 Introduction to Green Innovation

To understand what innovation means, one must first understand the definition of an invention. In the study of Artz, Norman, Hatfield, & Cardinal (2010) invention is defined as the creation of new products and processes through the development of new knowledge or the combination of existing knowledge. Innovation is a process of transforming an idea or invention into a good or service that will create value or for which the customers will pay a price. This will further satisfy the needs and expectations of the customers. Innovation is a popular field of study, looking at the fact that it has many different interpretable definitions. Many studies already studied the field of the changing industries and innovations. So, looking at innovation studies in general, it is known that innovations raise productivity and profitability, improve efficiency and reduce costs of investments of firms (Hsu, 2009). Rogers (1995) stated decades ago that innovations with greater advantages when compared to current products will lead to faster and more widespread adoption.

However, in that time there was not much attention for the impact of innovations on the environment. Most firms did not think about the positive impacts green innovations could bring, such as the advantage of lower emission that comes with a higher selling price. Russo and Fouts (1997) were one of the first that studied the environmental impacts. They state that corporate environmental management is of real importance. The rise of strict international regulation and conventions of environmental protection was because of the fact of growing attention towards the impact on the environment nowadays. Due to the upcoming awareness this led to a change of strategies and industries (Chen, Lai, & Wen, 2006). Lin, Tan, and Geng (2013) agree and state that innovation became important for increasing market shares and surviving the long run. Recently, Gürlek and Tuna (2018) found that successful green innovations improve market position, attract possible customers and gains competitive advantages.

Same as for innovation, the definition of the green innovation is also interpreted differently among studies. Due to the rise of awareness for the green part of innovation, the interest of studies that wanted to define green innovation also increased. For example, the definition of green innovation from the ISO 14031 standards, as stated by Chen et al. (2006), defines green innovation as hardware or software innovation that is related to green products or processes. This includes the technology innovations that are involved in energy-saving, pollution-prevention, recycling of waste, green product designs, or corporate environmental management. Although this description is sufficient, this study uses the quantitative literature review of Schiederig et al. (2012) to define green innovation, because this study compares and summarizes a diversity of definitions of green innovation used by the majority of studies within this field. They conclude that there are four interchangeable usable notions of green innovation and they find only minor conceptual differences between the definitions and therefore come up with a summarized definition, namely: "The innovation object may be a product, process, service or method and it should satisfy a user's need or solve a problem and therefore be competitive on the market. Regarding the environmental aspect it should reduce negative impact, and a full life cycle analysis and a thorough analysis of all input- and output factors must be done with the aim of a reduction of resource consumption and with an economical or ecological intention. This all is for setting a new innovation/green standard to the firm". To conclude, this allows dividing green innovation into green product innovation, green process innovation, green service innovation and green method innovation. These four parts will be described in more details in the next paragraph.

In today's society environmental awareness is becoming increasingly important. Many governments and thus firms have to deal with the impact of their operations on the environment. Firms could use green innovation to deal with the changing environment and at the same time increase their performance. Porter and Reinhardt (2007) state that the change of the environment has two ways of affecting firms. The first and most obvious one is through changing temperature and weather patterns. But, secondly, regulations also effects firms when, for example, the cost of emissions increase. Both have an influence on business inputs, access to related industries, and rules and incentives of rivalry. Of course, managers have to look after their firm by evaluating the effects of their operations on the environment. Tseng, Wang, Chiu, Geng, and Lin (2013) state that improving environmental performance and obeying environmental regulations contributes to the competitiveness of a firm. Firms must improve their green innovations, otherwise they weaken their competitiveness due to the rapidly changing green technology and the short life cycle of products. Aguilera-Caracuel and Ortiz-de-Mandojana (2013) acknowledge this as well and describe two different reasons why green innovation could help firms to be profitable, but also why it improves the quality of life. Firstly, green innovation can enhance preventive pollution. Firms could recycle and reuse materials and this will help a firm to save on operating costs. Next to that, environmental protection is a hot topic nowadays. So, firms could acquire a better ecological reputation if they show their green initiatives. A consequence is that such a firm could ask for premium prices and this greater social approval could also increase their sales. This allows firms to differentiate their products. Both reasons show a source of valuable opportunities.

So, green innovative studies agree that firms must introduce green innovation for having a sustainable future. The expectation of reputation improvement and of opportunities for innovation are the most important internal factors that drive the development of green innovation. The external factors concern environmental regulations, market demand and market stakeholder pressure, and networking activities (Dangelico, 2016). So, managers should know the importance of these factors. Porter and van der Linde (1995) name a few things managers could do to change their operations in order to reach that sustainable future. Firstly, they could measure direct and indirect environmental impacts instead of ignoring them. Secondly, they could learn to recognize opportunity cost of underutilized resources. Thirdly, they should create a positive bias towards innovation-based, productivity-enhancing solutions. And finally, they should be more proactive towards new types of relationships with regulators and environmentalists to get a new (greener) mind-set. Unruh and Ettenson (2010) also provide strategies to align a firm's green goal with their capabilities, namely accentuate, acquire, and architect. The first one involves playing up existing or latent green attributes in their portfolio. The second regards buying someone else's green brand. However, one needs to keep in mind the culture clash and the strategic fit. The third one contains the innovation of new green products. This is slower and more costly than the other two, but at the end it will be the best strategy, because it leads to valuable competencies.

Although different strategies exist to reach a sustainable future, all firms generally have the same goal, namely earning profits and surviving in the marketplace. To reach this goal, firms have to add value to the customers through the core business processes. One way to do this is by incorporating environmental concerns. Ultimately, this could lead to an improvement of a firm's overall efficiency and thus an increase in the performance and reduce in costs of the firm. However, every firm needs to tackle climate change differently and on their own way, as long as it reduces climate-related costs and risks. These approaches are mostly operational effective, but can also become strategic. But, for both they need to realize that carbon emissions are costly in order to reduce this. Implementing the best practices for reducing these costs is necessary to remain competitive. Firms could, for example, create environmentally friendly products, such as the reusable coffee cups[4], but could also restructure industries to cope with environmental impacts, or innovate activities that are sensitive to climate change. These

[4] Barrett, Clear. "What's the return on investing in a reusable coffee cup?" ft.com https://www.ft.com/content/edddb47c-0b22-11e8-839d-41ca06376bf2 (accessed November 28, 2018)

examples are forms of green innovation and this will lead to a better performance of the firm (Porter & Reinhardt, 2007).

2.1.1 Four types of Green Innovation

Because of the definition used in this study, green innovation can be divided into four types; green product, process, service, and method innovation. These four types will be used to describe green innovation on itself in more detail. Although, this study will make no further distinction between these types. It is also necessarily to mention that green product innovation completely dominates the other three types of green innovation for incorporating environmental concerns into corporate operations (Chan, Yee, Dai, & Lim, 2016). But in this section, for the sake of completeness, the four different types of green innovation will be substantiated consecutively.

First of all, starting with green product innovation, literature struggled with defining it. Yet several studies did try to come up with a definition or assumption. Back in 2004 the European Economic Interest Grouping (EEIG) concludes that product innovation has the largest impact on the environment. Poor product design and environmental regulations of developing countries could have negative impacts like waste issues (EEIG, 2004). Oke et al. (2007) agree and they provide a general definition of product innovation that matches the distribution used by the quantitative literature review of Schiederig et al. (2012). They describe product innovation as the offering of new products or improvements of existing products.

Regarding the green part, Reinhardt (1998) was one of the first to describe this definition. He simplistically expresses it as the kind of innovation that not only protects the environment, but also provides environmental benefits higher than conventional products. Moreover, Tseng et al. (2013) also look at the green aspect and go a step further. They divide green product innovation into five aspects, namely; the degree of new green product competitiveness understands customer needs, the evaluation of technical, economic and commercial feasibility of green products, the recovery of firm's end-of-life products and recycling, the use of eco-labeling, environment management system and ISO 14000, and the innovation of green products and design measures. Furthermore, to specify towards green product innovation, The Commission of the European Communities (2001) defines it as products that reduce the negative impacts and risks to the environment, utilize less resources and prevent waste generation during the phase of product's disposal.

Moreover, as most of the green innovative studies use a survey to measure green innovation, they name different classifications that could identify a green innovation. Chen et al. (2006) name a few items to measure green product innovation, namely; the firm chooses materials with the least amount of pollution, energy consumption, and resources for conducting the product development or design, the firm uses the fewest amount of materials, and the firm would use products that are easy to recycle, reuse, and decompose. Chiou, Chan, Lettice, and Chung (2011), Ar (2012) and Lin et al. (2013) state that whenever product innovation uses environmentally friendly materials, improves and designs environmentally friendly packaging for existing and new products, recovers a firm's end-of-life products and recycling, and uses eco-labeling, it could be called green product innovation.

Furthermore, less study has been done to green process, service, and method innovation, Oke, Burke, and Myers (2007) study process and service innovation and define process innovation as creating or improving methods of production, service or administrative operations as well as developments in the processes, systems and reengineering activities undertaken to develop new products. They describe service innovation as new developments in activities to deliver the core product and make it more attractive to consumers. They acknowledge the study of Klassen and Whybank (1999) as they state that green process innovation is any adaptation to the manufacturing process that reduces the negative impact on the environment during material acquisition, production, and delivery. Moreover, Chen et al. (2006) use ISO 14031 standards to define green process innovation as the performance in process innovation that is related to energy-saving, pollution-prevention, waste recycling, or no toxicity (Lai et al., 2003). Green process innovation is used to increase the performance of environmental management and this helps protecting the environment. Similarly, Chiou et al. (2011) also operationalize green process innovation. They state that whenever an process innovation has a low energy consumption during production, use, and disposal; recycle, reuse, and remanufacture material; and use cleaner technology to make savings and prevent pollution, it could be labeled as green process innovation.

Regarding green method innovation, Schiederig et al. (2012) describe that, for example, green business models or marketing methods are meant by this. Chiou et al. (2011) have made an effort to operationalize green managerial innovation, which is comparable with green method innovation described by Schiederig et al. (2012). They name redefining operation and production processes to ensure internal efficiency and re-designing and improving product or service to obtain new environmental criteria or directives as measurements of green managerial innovation (Chiou et al., 2011). Unfortunately, other studies did not study this type of green innovation due to the fact that it is tremendously difficult to measure the impact of it.

In summary, it can be stated that the main type of green innovation is green product innovation. Many previous studies were interested in only this type of green innovation and its impact on the performance of a firm and used a survey to gather their data. However, this study will use an unbalanced panel dataset that unfortunately cannot make a distinction between these types. So, this study will look at green innovation in general and therefore contributes to literature as most previous studies only look at green product innovation.

2.2 Theories on innovation

The field of green innovation is quite new, so there have not been many theories on the green part of innovation yet. However, of course the field of innovation itself is been widely studied and many theoreticians have already described their theories on innovation. This study will substantiate them and will make a link to the green part of innovation.

2.2.1 Innovation Theory

Back in the 30's of previous century, far ahead of the awareness of climate change, Schumpeter (1934) defined an innovation theory where many innovation studies are based on. He was the first to explicitly research innovation (Santos, Basso, Kimura, & Kayo, 2014). In his study, he describes innovation as the creation of new knowledge, or the transformation of new combinations of existing knowledge into innovation within the organization. This perspective could be explained by five types of innovation: new product, new process, new markets, new input sources and new industrial structures. These five types have two sides of innovation; radical and incremental innovation. The first are innovations originating from the process of creative destruction, such as technological discoveries, shifting to something completely new that could be associated with a product or process. The latter is the continuous improvement process that aims to consolidate radical changes and to strengthen the market position (Santos et al., 2014). The innovation theory of Schumpeter explains that adaptable firms that try new creative ways of operating are more likely to outperform firms that do not, especially in a competitive environment. He states that trying new ways of using a firm's knowledge, technology and resources brings new opportunities that ultimately could lead to a stronger market position. Schumpeter describes these changes as a dynamic process of 'creative accumulation'. Therefore, innovation brings new levels of economic performance for all industries and this could be explained by the inputs to and outputs of innovation, namely R&D intensity and patent intensity respectively (Choi & Williams, 2013).

2.2.2 Contingency Theory

Next to Schumpeter's theory as the foundation of innovation theories, many studies also use the contingency theory (Sousa & Voss, 2008). The theory explains the firm as a complex organization of individuals and focuses on analyzing the firm its internal structure and the relationship among departments and units (DeCarolis & Deeds, 1999). This theory helps explaining the behavior of organizations, because it states that organizations adapt their structures in order to keep up with the changing contextual factors, so that it reach high performance. There is no best way to organize or lead a firm. The process of decision making differs across firms, but the impact of the same decisions also differ across firms. For a contingent manager or leader it is all about applying their own style to the right situation. Morgan (1998) describes that organizations are open systems. These systems need thoughtful management for internal needs and to be able to adapt to environmental elements, without having a best way of tackling this. However, there are three theoretical and practical contributions of this theory. Firstly, one needs to identify important contingency factors that distinguish between contexts. Secondly, one needs to group different contexts based on the contingency factors. Thirdly, one needs to determine the most effective internal organization designs or responses in all of the different contexts groups.

So, this theory defines three types of factors, namely contextual, response and performance factors. These will be substantiated by linking this to the field of green innovation. The first refers to the exogenous situational characteristics that could influence the organization. In most of the cases, these factors are hard to control or manipulate, but a manager with enough effort could change the impact of it in the long-term (Sousa & Voss, 2008). Examples of a contextual factor are environmental dynamism or market demand (Lin et al., 2013). But, the most interesting contextual factor is the pressure of environmental regulations (Chan et al., 2016). These regulations are rapidly changing. So, if firms are not constantly adapting to these regulations, they will weaken their competitiveness (Tseng et al., 2013). One way of adapting to this is by investing in green innovation. This is an example of the second factor, which refers to the actions taken by the organizations in response to the contextual factors. Chan et al. (2016) argue that green innovation and environmental regulations cannot be separated. The latter are unstable and uncertain yet inevitable in today's society. So, they consider green product innovation as a positively associated consequence of the pressure of environmental regulations and policies. Regulatory pressure is one of key drivers for firms to develop a sustainable future. Regulatory pressure itself does not lead to an increase in firm performance. Therefore, managers have to convert these pressures by using (e.g.) green innovation. Many studies within this field are interested in at least green innovation as the response to these contextual factors. Although, most of the studies do not test for the relationship between them, but only between the response and the third factor; the performance factor. The performance measures the effectiveness of the response factor subject to the contextual factor. Most of the studies within this field are mostly interested in firm performance or competitive advantage as the performance factor.

Sousa and Voss (2008) state that according to the contingency arguments, an organization should use practices that are both effective to a high degree and ineffective to a low degree. This is in line with the perspective of practices being adopted due to efficiency factors to directly improve performance. However, this does not explain when a firm has non-efficiency drivers of adoption or when it focuses on building capabilities as the alternative source of performance. Therefore, they name the institutional theory and resource-based theory respectively as promising theories that address the limitations of the contingency theory.

2.2.3 Institutional Theory

The institutional theory considers the structures of an organization as authoritative guidelines for social behavior. The institutional theory argues that practices could also be adopted due to non-efficiency instead of efficiency like the constitutional theory describes. In this way, a firm could gain legitimacy whether or not the practices may lead to a performance increase (Sousa & Voss, 2008). Aguilera-Caracuel and Ortiz-de-Mandojana (2013) describe that studies use the institutional theory to study the adoption and diffusion of organizational practices among organizations. Organizations with the same environment will have similar practices and motives and will thus correspondent with each other. These practices become institutionalized and thereby the society will adopt them and see them as legitimate. This means that countries will regard and respond differently to environmental issues based on the two dimensions described by the institutional theory (Hoffman, 1999). The first dimension is called the regulatory dimension and refers to the existing laws and rules in a particular national environment that promote certain types of behavior and restrict others (Kostova, 1999). The second is called normative dimension and refers to the cultural values, beliefs, and goals of the society regarding organizational behavior (Kostova & Roth, 2002). Linking this to the study means that one could expect differences between countries for the effect of green innovation on firm performance.

2.2.4 Resource-based Theory

The resource-based theory defines that not all resources are of the same importance and not all of them will become a source of a sustainable competitive advantage. Because, it depends on whether the resources could be imitated or substituted. So, the performance of a firm results from valuable resources that are difficult to obtain and hard to imitate or trade. This explains why firms not always adopt efficient practices from other firms, but rather invest in other sources of performance advantage (Sousa & Voss, 2008).

So, a manager or leader of an organization must identify the potential key resources of a firm and find out whether these resources are valuable, rare, not imitable and not substitutable. Examples of these intangible resources are brand names, skilled employees, machinery, and capital (Cho & Pucik, 2005). The resource-based theory substantiates that the unique resources and capabilities of a firm are the key drivers of competitive advantage and business performance. The manager of the firm must cultivate these capabilities and deploy them in product-market strategies to strive for this advantage (DeCarolis & Deeds, 1999). Green innovation is such a unique capability and thus a key driver of firm performance within this study. Hart (1995) is one of the key theoreticians of this theory and he states that capabilities that avoid pollution, ensure sustainable development and generate environmental solutions provide competitive advantage to a firm. The theory defines that competitive advantage leads a firm to perform better than its competitors, because a firm could have relatively lower operating costs or could differentiate itself. When green innovation is successful it could make imitation more difficult, which allows firms to sustain their competitive advantage longer and thus increase their firm performance (Chang, 2016).

2.3 Empirical Evidence

Previous studies already studied the field of green innovation. Overall, these studies stimulate the strategic approaches a firm could take to reduce emissions by stating that it will, next to helping the environment, increase the performance of the firm (Olson, 2014). It will provide them social, environmental and economic benefits. Kim, Moon and Yin (2016) partly agree with Olson by stating that on the one hand environmental management leads to become competitive and gain legitimacy, which leads to a better performance of a firm. But on the other hand, it could create additional costs, such as the costs of solid waste disposal, which have a negative influence on firm performance (Palmer, Oates, & Portney, 1995). Multinational firms have a hard time developing sustainable green strategies to meet the demands of stakeholders, which makes it an interesting field of study.

This section will be based on the factors described by the contingency theory to fully describe green innovation as the center of research. Firstly, the antecedents of green innovation will be described. These are similar to the contextual factors defined by the contingency theory. Of course, there are many different ways for a manager or leader to make a decision to respond to these factors and there is no best way. One could, for example, move the headquarter of the firm to another country when national regulations are too strict. But, this study only focuses on green innovation as the response action. Although firm performance will be the performance factor of this study, competitive advantage will also be outlined for the sake of completeness.

2.3.1 Antecedents of Green Innovation

Antecedents, or as the contingency theory calls them; contextual factors, should not be overlooked. The most interesting antecedent is the pressure of environmental regulations (Chan et al., 2016). Porter and van der Linde (1995) were one of the first to describe that many firms could open up new market segments and determine higher prices for green products by carrying out the opportunities that reduce pollution through innovations that redesign products, processes, and operations. Firms that succeed in becoming green will be distinguished by their commitment to being environmental sustainable and to the performance of their green products (Unruh & Ettenson, 2010). However, firms will more often not go for these opportunities without environmental regulation that pushes them. This is because of the fact that managers often do not have complete information and unlimited time and attention. There are too many barriers to change into a more environmentally friendly business. This means that these kinds of regulations play an important part in green innovation. Bad regulation could damage competitiveness, while good regulation could enhance it. Environmental regulations provide opportunities for firms to increase their green product innovation as it is the most important external driver for the development of green innovation (Chan et al., 2016; Dangelico, 2016). So, policies regarding environmental regulations should become stricter to encourage greener innovations.

Moreover, Chan et al. (2016) describe that the pressure of environmental regulations/policies pushes firms into a more sustainable development. These pressures may not directly lead to a better firm performance. However, they are directly related to green innovation, because these pressures are inevitable. Therefore, they hypothesize whether the pressure of environmental regulations/policies is positively associated with green product innovation. These regulations include national and regional regulations on the environment, on resource saving and conservation, but also on products that potentially conflict with laws. Their sample consists of 250 operations managers from the operating industry in China that who have completed the survey between April 24 and May 8 in 2015. They find a positive relation that is significant at the 1% level between the pressure of environmental regulations and green product innovation. This means that the managers of these firms use green product innovation as a response to these regulations as it converts these pressures into a better environmental performance.

Furthermore, Chiou et al. (2011) use another antecedent of green innovation, namely greening the supplier. This is in line with the argumentation of environmental regulations and policies described by Chan et al. (2016), because customers and buyers require their suppliers to also have environmentally friendly products and materials. Firms need to cooperate with suppliers early in the product development process, because in this way they could reduce the negative impacts on the environment. So, they test whether greening the supplier is positively associated with green product, process, and even managerial innovation. Chiou et al. (2011) state that a firm could do a few things to encourage their suppliers to go green. They could encourage them by requiring and assisting suppliers to obtain a third-party certification of environmental management system, by providing environmental awareness seminars and training for suppliers, by providing environmental technical advice to suppliers and contractors in order to help them to meet the environmental criteria, by inviting suppliers to join in the development and design stage, and/or by sending in-house auditor to appraise the environmental performance of the supplier. Their sample consists of 124 respondents from the purchasing department of firms in Taiwan. The results report that greening the supplier is positively related and significant at the 1% level to all three parts of green innovation. So, the results show that if firms have used at least one of the ways to encourage their suppliers to go green, it has led to internal green product, process and method innovations. So, firms should work together with their suppliers to become more environmentally friendly.

Another antecedent of green innovation is market demand. Lin et al. (2013) state that especially green product innovation is being adopted to meet market demand and to gain a competitive advantage. The key elements of market demand are customer benefit and price, and customer preference can be influenced by the price of the product. However, although many customers want firms to produce green products, they do not align their actual purchasing behavior with these requirements. Finding balance between these factors in order to meet market demand is still difficult for many firms. When firms notice a gap between supply and demand in the market, they could respond to this by having successful green innovations, meaning that these innovations are critical to survive and improve market position. Therefore they hypothesize that market demand is positively associated with the three types of green product innovation performance. They define market demand by the segmentation of the market, by the requirements about green products of the customers, by the price flexibility of demand for green products, and by the customer benefits for these green products. The study uses a sample of 208 respondents that are a CEO, director, or manager of a Vietnamese firm operating in the motorcycle industry and filled out the survey between January and July 2011. They indeed find a positive relationship between market demand and the three types of green product innovation performance. Unfortunately, they do not report the level of significance. So, manufactures should understand the market demand. Because, if a firm manages its market demand well, then its green product innovation performance will improve.

Lastly, Gürlek and Tuna (2018) are interested in the antecedent factor green organizational culture, because firms with a green organizational culture could contribute to further protection of the environment. Environmental regulations and policies alone are not sufficient enough. A firm also has to develop a green organizational culture to make green innovations into a success. Therefore they hypothesize the positive effect of green organizational culture on green innovation. They define green organizational culture as a set of shared mental assumptions that guide interpretation and action in organizations by describing appropriate behavior in different kind of situations. Their sample consists of 545 employees or managers of four- and five-star hotel companies in Antalya that filled out the survey in August 2016. The results reveal that green organizational culture has a positive on green innovation as this relationship is significant at the 1% level. This means that a green organizational culture is an important antecedent of green innovation as it shapes the actions regarding the environment.

The antecedents of green innovation have a positive effect on green innovation when a firm uses it as a response to them. So, many firms will do well by going green. Although, some have a more proactive attitude by greening the supplier and others need the push of inevitable environmental regulations to go green.

2.3.2 Impact of Green Innovation on Competitive Advantage

Competitive advantage is one of the two main performance factors green innovation has. This section will introduce the performance factor first and then describe the empirical evidence of the link between green innovation and competitive advantage done by other studies.

Back in the days many businesses had a general negative view of green innovation. They thought that investing in the protection of the environment was harmful to their businesses. Because, the inefficiently use of resources results in unnecessary waste, defects, and stored materials. This can be seen from scrap, harmful substances, or pollution. Firms may think that helping the environment will bring additional activities that add costs but create no value for customers, such as the handling, storage and disposal of waste. The bottom line is that managers should not focus on these actual additional costs, but focus on including the opportunity costs of pollution. Environmental improvement and competitiveness come together and managers must recognize environmental improvement as economic and competitive opportunities instead of additional cost or inevitable threats. The early movers will have the major benefits. So, environmental innovation has two sides of the trade-off, namely the side of the social benefits arising from environmental standards and the side of industry's private costs for prevention and cleanup, which means higher prices and lower competitiveness. However, properly designed environmental standards could trigger innovations that lower these costs and therefore improve the value of the product. Firms could use inputs more effectively and productively for improving environmental impact and this makes firms more competitive (Porter & van der Linde, 1995).

Yet, the study of Chen et al. (2006) states that environmental pressure is something all businesses have to deal with these days and this asks for a professional attitude towards managing this. Businesses do not have to avoid this, because these pressures could be turned into unique competitive advantages by carrying out green innovation. Next to that, proactive strategies in green innovation also prevent firms from facing environmental protests or penalties and it helps them developing new market opportunities. They define this corporate competitive advantage as "the firm occupies some positions where the competitors cannot copy its successful strategy and the firm can gain the sustainable benefits from this successful strategy".

So, Chen et al. (2006) declare that green innovation increases resource productivity to make up with the environmental costs. Besides, businesses will also have first-mover advantages, so they could ask for higher prices for green products. This will lead to a better image, selling their green technologies and services and the creation of new markets (Porter & van der Linde, 1995). Chang (2016) also points out that a firm's resources could provide competitive advantage when these are valuable, unique, and imperfectly imitable. Having a better capability of using these resources could decrease the difficulty of adjusting to future changes. The environmentally impact on the economy is increasing, so firms should have an environmental vision and management. The latter takes care of conveying the environmental goals. However, Li, Su and Lin (2010) argue that many fail to recognize the fact that many competitors and imitators actually have profited more from the innovation. Both studies have a fair point, but green innovation will only lead to competitive advantage when it could not be imitated.

Regarding empirical evidence, Chen et al. (2006) study green innovation for firms operating in information and electronics industries in Taiwan and their sample consists of 203 managers in manufacturing, marketing, R&D, or environmental protection departments that filled in the survey. They divide green innovation into green product innovation and green process innovation and hypothesize that the performance of green product and process innovation is positively associated with corporate competitive advantage. They state that a firm has competitive advantage when a firm occupies some positions where competitors cannot copy their strategies while this strategy brings the firm benefits. Their measurement of competitive advantage contains of eight strategies in which a firm could score relatively better than competitors to (partly) have competitive advantage over their competitors, namely; lower costs, higher quality of products or services, more capable of R&D and innovation, better managerial capabilities, better profitability, exceeding growth of the firm, being a first mover and occupying important positions, or a better corporate image. They find a positive relation between green innovation and competitive advantage for both green product and process innovation. This relationship is significant at the 5% level for green product innovation and at the 1% level for green process innovation. The study did not found any general significant differences between green product and process innovation. Although, it had some industrial differences. Thus, increasing green product and process innovation will lead to stronger corporate competitive advantage and this performance is helpful to businesses.

Moreover, Chiou et al. (2011) follow and broaden the definition of green innovation as used in Chen et al. (2006) and also test whether it is positively related to competitive advantage. This study also uses firms in Taiwan as a sample, but this study aimed to extend their study beyond a single sector in Taiwan. They state that customers are becoming more environmentally conscious and firms have to respond to this by introducing green innovation to meet market demand and gain competitive advantage. They measure competitive advantage by a firm its customer response, product design and innovation, quality of products and services, and low production costs. While using the sample of 124 respondents from the purchasing department of firms in Taiwan they find positive relations between green product, process, and method innovation and competitive advantage as well. These three relationships are all significant at the 1% level, concluding that firms could gain competitive advantage by implementing green innovation. This means that by implementing green innovation firms have lower production costs, increased productivity and efficiency, better product and service quality, and a better response from customers that leads to an improvement of competitive advantage.

Furthermore, Gürlek and Tuna (2018) also describe the conflict that environmental protection activities could have a negative effect on firms. The solution that was often used was abandoning the green or green washing. However, green innovation could be a better solution, because these innovations give the opportunity to both protect the environment and increase competitive advantage. The study substantiates that high green innovation creates competitive advantage for the organization, because it provides a strategy that many competitors cannot take over, which provides them more financial benefits. These organizations gain the advantage of differentiation and the advantage of cost savings. A win-win solution which increase product value and decreases the costs of environmental effects (Porter & van der Linde, 1995; Chang, 2016). They study four- and five-star hotel firms in Antalya and test whether green innovation has a positive effect on competitive advantage. They use the same items used by Chen et al. (2006) to measure competitive advantage and they find that green innovation has a positive effect on competitive advantage as well. This relationship is significant at the 1% level. This means that green innovation provides a strategy competitors cannot perfectly imitate and this leads to more financial benefits compared to their competitors.

Moreover, Frenken and Faber (2009) state that environmental innovation is of great importance regarding being sustainable. Ar (2012) agrees and adds to this that green innovation is increasingly important for firms to show they are aware of the environmental impacts by producing non-hazardous and non-toxic products. He studies the largest 1000 exporters explained by Turkish Exporters Assembly for 2010 and checks whether green product innovation has a positive influence on competitive capability. Although he names it competitive capability instead of competitive advantage, he means the same. Because, he measures it by similar items, such as if the products could not be easily substituted, the arrival of new competing products, and the time of products becoming obsolete, which correspondents to the imitability of products. He finds a positive relationship between green product innovation and competitive capability and this relationship is significant at the 1% level. Ar checked if this relationship is stronger for managers with high environmental concerns as well, but that was not the case.

Pujari (2006) also agrees by stating that green innovation is portrayed as an opportunity and more and more firms are going to see that. However, the study argues that it is uncertain whether green innovation truly achieves market success. Lin et al. (2013) take away this uncertainty and state that firms need green innovation as an opportunity to reduce the negative influences of production on the environment. They acknowledge that this will lead to competitive advantage which ensures a larger market share (Dangelico & Pontrandolfo, 2010). Olson (2014) adds that green product innovation has the advantage of not relying on system redundancy for reliability compared to conventional innovations. Widely adopted green innovations also provide non-green user benefits. Successful green innovations will compensate conventional innovations which makes it financial attractive and only these innovations can have significant positive impacts on the environment. Improving product design and quality leads to higher prices and higher profit margins. Green product innovation increases resource productivity by saving on materials, lowering energy consumption, increasing the recycling of waste and reducing the use of the resources. That is why environmentalists and government policy makers promote green innovation and they usually use three main reasons. Firstly, they state that non-green innovation have unfair advantages, because of the failure to pay for dealing with greenhouse gases. Secondly, new green innovations require start-up subsidies, otherwise it could not compete with older non-green innovations. Thirdly, green subsidies lead to high value green industries and jobs (Olson, 2014).

To summarize, green innovation could turn environmental pressures into competitive advantages, but only when these are valuable, unique, and imperfectly imitable. Otherwise, the competition could just copy it and profit more from it. Previous studies indeed find a positive relationship between green innovation and competitive advantage and most of these relationships are significant at the 1% level. These studies name being the first-mover and demanding higher prices as the main reasons for this positive effect.

2.3.3 Impact of Green Innovation on Firm Performance

Other studies name firm performance instead of competitive advantage as the most important performance factor, because some doubt whether competitive advantage is a real performance factor at all as it may lead to firm performance. Meaning that firm performance could be seen as a consequence of competitive advantage and thus a more fitting performance factor (Ar, 2012; Gürlek & Tuna, 2018). Although, many studies use a different name for firm performance, they almost all mean practically the same. Again, this section will describe the performance factor and the empirical evidence of the link between green innovation and firm performance done by other studies.

Some studies only studied the impact of green product innovation on firm performance, because this type of green innovation has the largest part in green innovation and is therefore easier to measure. Lin et al. (2013), for example, studied green product innovation in the

Vietnamese motorcycle industry. They state that with green product innovation firms could gain sustainable development and achieve their business targets. So, they emphasize that green product innovation and firm performance should incorporate considerations related to the knowledge of market demand. The study divides green product innovation performance into three main aspects, namely environmental performance, products, and economic performance and hypothesizes that all three kinds are positively associated with firm performance. Because of using a survey, they measure firm performance by checking if a firm's market position improves and if a firm's sale volume, profit rate, or reputations enhances (Li et al. 2010). They indeed find that all three kinds are positively associated with firm performance. Unfortunately, as already stated, they do not report the level of significance. So, if a firm manages the market demands well, then the performance of the green product innovation and thus the performance of the firm will improve, which leads to a better market position and reputation.

Moreover, Ar (2012) also substantiates why there is a relationship between green product innovation and firm performance, because he finds that a change in a regulatory policy may affect green product innovation and thus firm performance. He hypothesizes that there is a positive relationship between green product innovation and firm performance. Because, this type of innovation encourages using raw materials efficiently and this results in lower costs for these materials what eventually leads to new ways of converting waste into saleable products to increase cash flow, competitive advantage and thus firm performance. He measures firm performance by sales growth, market share, and return on investment. With his sample of the largest 1000 exporters explained by Turkish Exporters Assembly for 2010 he finds a positive relationship between green product innovation and firm performance for all three measurements of firm performance and all significant at the 1% level. Combining this results with his antecedent factor shows that firms should take into account changes in regulatory policies that may affect green product innovation, because this may result in a better firm performance. The positive relation between green product innovation and firm performance demonstrates the strong influence of green product innovation and this confirms previous literature (Pujari, 2006; Chen et al., 2006; Chiou et al., 2011).

Similar to Lin et al. (2013) and Ar (2012), Chan et al. (2016) also study green product innovation. However, they divide firm performance in firm profitability and cost efficiency. These two represent the major visions of firms, because most of the firms are either pursuing premium prices or cost-oriented. They name green product innovation a direct consequence of the pressure of environmental regulations and policies and hypothesize whether green product innovation is positively associated with firm profitability and cost efficiency. They measure profitability with profit/loss, return on assets, profit margin, and return on equity. Regarding cost efficiency, they name products with low costs, low inventory costs, low overhead costs, and an offer price as low or lower than competitors as items that measure it. With their sample of operation managers from the industry operating in China they find a positive relationship for both firm performance indicators and both are also significant at the 1% level. These results in combination with the positive significant relationship between the pressure of environmental regulations/policies and green product innovation prove that, because of environmental pressure, firms could develop green product innovations, which is a key capability for competitiveness that will increase firm performance (Porter & van der Linde, 1995). So, managers have to align their firm's activities with (e.g.) green product innovation to cope with these pressures in order to increase their firm performance. But, policy makers could also learn from these results. They need to consider the practical implications when setting up environmental regulations, because otherwise the responsibility would only blindly shift to the manufacturers. In the future, many firms that are unable to innovate will not survive and this affects the economy of the whole country.

Next, Aguilera-Caracuel and Ortiz-de-Mandojana (2013) study green innovative firms that have registered a higher percentage of green patents at EPO for the past 20 years and use a matched-pairs sample of pairs of 88 green innovative and 70 non–green innovative firms with green patents granted by EPO. They state that green innovation is one of the most proactive ways of achieving the benefits of environmental development. Green innovative firms could enhance their firm performance by using two complementary mechanisms. Firstly, by implementing green innovation firms could improve their reputation and legitimacy through external agents. This will lead to an increase in their revenues. Secondly, green innovative firms are always looking for improvements in green management processes to improve the performance and reduce the operating costs. Therefore, they hypothesize that green innovative firms experience a greater improvement in financial performance than non-green innovative firms. They measure the improvement of firm performance by the change of return on assets for two consecutive years. They analyzed the improvement of firm performance during the period of 2008-2010 and find that firm performance is indeed higher for green innovative firms than for non-green innovative firms. This is significant at the 10% level. Although, the improvement of firm performance is not higher for green innovative firms than non-green innovative firms as they find no significant relationship. They give some reasons why this could be the case. For example, it takes time before green innovative firms could potentially improve their firm performance, not all green innovative firms have the necessary conditions to improve their firm performance.

Same as Aguilera-Caracuel and Ortiz-de-Mandojana, Li et al. (2010) also study Chinese firms and the field of innovation and firm performance, but not the green aspect. So, logically, their variable product innovation is a combined variable of green product innovation and non-green product innovation. They state that product innovation improves market position compared to competitors, creates entry barriers, establishes a leadership position, creates new distribution channels and customers and therefore increases the performance of a firm. Therefore, they hypothesize that there is a positive relationship between product innovation and firm performance. In this study firm performance is measured by market position, sales volume, profit rate, and reputation. Their results support this relationship significantly at the 1% level, which means that product innovation is beneficial for the performance of a firm. So, top managers should include product innovation in their strategies.

Lastly, Chiou et al. (2011) study firms in Taiwan, but call it environmental performance and hypothesize whether the three forms of green innovation, namely product/process/managerial, have a positive relationship with environmental performance. They measure this performance by the level of hazardous waste and emission reduction, the level of water, electricity, gas, and petrol consumption, and the improvement of environmental compliance. They find support for the positive relationship between green product/process innovation and environmental performance significant at the 1% level, but not with green method innovation and environmental performance as this relationship is not significant and even shows a slightly negative sign. The reason could be that green managerial innovation has a more indirect effect on a performance variable. This makes it interesting to check whether this variable have an indirect impact on the relationship between green innovation and a performance factor. This will be further explained in paragraph 2.3.4.

So, overall studies find a positive relationship between green innovation and firm performance significant at the 1% level. This concludes that green innovation ensures lower material costs, improves the position in the market compared to competitors, creates new channels of distribution and attracts new customers. This all leads to an improvement of the performance of a firm.

2.3.4 Moderating impacts on the relationship of Green Innovation and performance factors

There could also be indirect impacts on the relationship between green innovation and a performance factor, the so called moderation effect. It could occur when the relationship between green innovation and the performance factor depends on a third factor, the moderator. This factor changes the strength or direction of the effect of the relationship.

Most of the studies within the field of innovation that test for other impacts on the relationship between green innovation and performance factors test for the effect of moderators. For example, Aguilera-Caracuel and Ortiz-de-Mandojana (2013) study whether there is a moderating effect on the relationship between green innovation and the financial performance improvement of green innovative firms and test for two moderators, namely stringent environmental regulations and environmental normative level. The first includes the challenges environmental regulations contain, because these regulations are difficult to implement, are inefficient, and differ in stringency for each country. This could cause disadvantages for the profitability of firms. Thus, they hypothesize that the more stringent the environmental regulations are in a country, the lower the positive relationship will be between green innovation intensity and the financial performance improvement of green innovative firms. The stringency of environmental regulations is measured by the regulation levels of air pollution, toxic waste disposal, water pollution, chemical waste, clarity and stability, flexibility, and innovation, but also by leadership in environmental policies and the consistency of regulation enforcements. They find a negative moderating effect significant at the 10% level. This means that the greater the stringency of environmental regulations in a country, the lower is the probability that green innovation will lead to better financial performance improvement. The second includes that countries where environmental issues are relevant will appreciate environmental improvements in firms. Because they did not find that the improvement of firm performance is significantly higher for green innovative firms than non-green innovative firms, they concluded that not all green innovative firms have the necessary conditions to improve their firm performance. Thus, they hypothesize that the higher the level of environmental norms in a country, the greater the positive relationship between green innovation intensity and financial performance improvement of green innovative firms. They indicate this by the level of contribution of the public sector to international and bilateral funding for environmental projects and development aid. However, they do not find a significant moderating effect. This could be because the majority of societies are still too concerned with environmental regulations.

Next to that, Chan et al. (2016) also test for the effect of a moderator, environmental dynamism, on the relationship between green product innovation and the two measurements of firm profitability. They describe this moderator as frequent and rapid changes induced by technology, customers, and suppliers. The significant moderating effect of environmental dynamism makes clear that managers should consider these changes when designing green innovative products in a dynamic environment, because it could increase firm performance. They find this positive relationship significant at the 1% level for the first measurement of firm performance, namely cost efficiency, and conclude that this relationship is stronger in an environment characterized by high dynamism. For the second measurement, firm profitability, they only find marginal support as the significant level is 10%, but still enough to confirm the relationship. So, firms could better improve their firm performance under a dynamic circumstance, but the improvement is found to be more for cost efficiency than for firm profitability. However, they also note that these results might be influenced, because cost efficiency is easier to measure than firm profitability.

More interestingly for this study is the study of Ar (2012). He uses managerial environmental concern as a moderator variable on the relationship between green product innovation and firm performance and between green product innovation and competitive capability. The study states that the more the commitment of management towards innovation, the more the willingness of the implementation of green innovations as it is one of the most important factors of innovation. He measures it by checking whether the environmental innovation is not necessary to achieve high levels and an important and effective component of strategy, and whether most environmental innovations are worthwhile. He finds a stronger relationship between green product innovation and firm performance in high managerial environmental concern than in low managerial environmental concern as this relationship is positively significant at the 5% level. However, this result was not found in the relationship of green product innovation on competitive capability from the level of managerial environmental concern. A possible explanation could be that product innovation activities may not lead to competitive capability although firms seek competitive advantage firstly through product innovation. Sectorial differences and competition level in the sector could be possible reasons. Unfortunately, the results of the study of Ar (2012) do not focus on these sectorial differences (Friar, 1999). He also does make a statement that further research should include other moderator variables such as environmental regulation or environmental policy.

There are many other impacts on the relationship between green innovation and a performance factor that could be examined. However, almost none of the impacts that have already been tested has good substantiated or strong significant empirical evidence. Next to that, all of these other impacts are measured by using a questionnaire, because there is no data available to measure it. So, therefore investigating such an impact on the aforementioned relationship will be left out of this study.

2.3.5 Overview field of study

To summarize, the majority of studies with empirical evidence of a relationship between green innovation and firm performance or similar performance factors conclude that there is in fact a positive significant relationship between green innovation and these performance factors. Some studies divide firm performance in more specific firm performance factors and environmental performance is one of them (Chiou et al., 2011; Lin et al., 2013). However, this study focuses on the financial part of firm performance: economic performance. Therefore, it is important to mention that this study will express economic/financial firm performance as firm performance. Table I and Figure I give an overview of the most used factors and relationships that have to do with green innovation. Of course, there are many more and most of the factors could also be split into more specific factors. Appendix A gives an overview of these factors. Next to that, table II gives an overview of the costs and benefits of green innovation.

Moreover, most of the studies within the field of green innovation use a survey to gather their data, because green innovation is difficult to measure. A problem that arises when one uses a survey is the non-response bias between the groups of respondents, although this could be solved easily. However, a limitation it brings is the limited choice of research methods one can use to test the hypothesis, because of the fact that green innovation will not be directly observable while using a survey. This will be explained in paragraph 3.2. Next to that, many of the surveys done by other studies only focus on green product innovation as this is the easiest one to measure with this method of data gathering. By using patent data, like this study, it is able to not only use green product innovation, but also include green process, service, and method innovation. Therefore, this study contributes to the literature.

Panel A

Antecedents		Responses		Performances	Hyp.	Acc.?	Literature
Green organizational culture	→	Green innovation			+	Yes	Gürlek & Tuna, 2018
		Green innovation	→	Competitive advantage	+	Yes	Gürlek & Tuna, 2018
Pressure of environmental regulations/policies	→	Green product innovation			+	Yes	Chan et al., 2016
Greening the supplier	→	Green product innovation			+	Yes	Chiou et al., 2011
Market demand	→	Green product innovation			+	Yes	Lin et al., 2013
		Green product innovation	→	Competitive advantage	+	Yes	Chen et al., 2006; Chiou et al., 2011
		Green product innovation	→	Competitive capabilities	+	Yes	Ar, 2012
		Green product innovation	→	Firm performance	+	Yes	Ar, 2012; Aguilera-Caracuel & Ortiz-de-Mandojana, 2013; Lin et al., 2013; Chan et al., 2016
		Green product innovation	→	Environmental performance	+	Yes	Lin et al., 2013
Greening the supplier	→	Green process innovation			+	Yes	Chiou et al., 2011
Market demand	→	Green process innovation			+	Yes	Lin et al., 2013
		Green process innovation	→	Competitive advantage	+	Yes	Chen et al., 2006; Chiou et al., 2011
		Green process innovation	→	Environmental performance	+	Yes	Chiou et al., 2011
Greening the supplier	→	Green method innovation			+	Yes	Chiou et al., 2011
Market demand	→	Green method innovation			+	Yes	Lin et al., 2013
		Green method innovation	→	Competitive advantage	+	Yes	Chiou et al., 2011

Panel B

Responses	Moderators	Performances	Hyp.	Acc.?	Literature
	Environmental dynamism		+	Partly	Chan et al., 2016
	Stringent environmental regulations		-	Yes	Aguilera-Caracuel & Ortiz-de-Mandojana, 2013
	Environmental normative level		+	No	Aguilera-Caracuel & Ortiz-de-Mandojana, 2013
Green innovation	↓ →	Firm performance			
	Managerial environmental concern		+	Yes	Ar, 2012
Green product innovation	↓ →	Firm performance			
	Managerial environmental concern		+	No	Ar, 2012
Green product innovation	↓ →	Competitive capability			

Table I: Overview Empirical Evidence of Green Innovative Studies. Gives an overview of the empirical evidence of green innovative studies within the scope of field. Panel A consists of direct relationships, wherein "Antecedents", also called contextual factors, stand for the exogenous situational characteristics which can influence the organization, "Responses" stand for the actions taken by the organization in response to the antecedents, and "Performances" stand for the performance factors that measure the effectiveness of the response factor subject to the antecedent. Panel B consists of the indirect impacts on the direct relationships of panel A, wherein "Moderators" stand for the factors that change the strength or direction of the effect of the relationship. "Hyp." stands for the hypotheses opposed by the literature, "Acc.?" stands for whether the hypothesis is accepted or not, and "Literature" stands for the supporting literature.

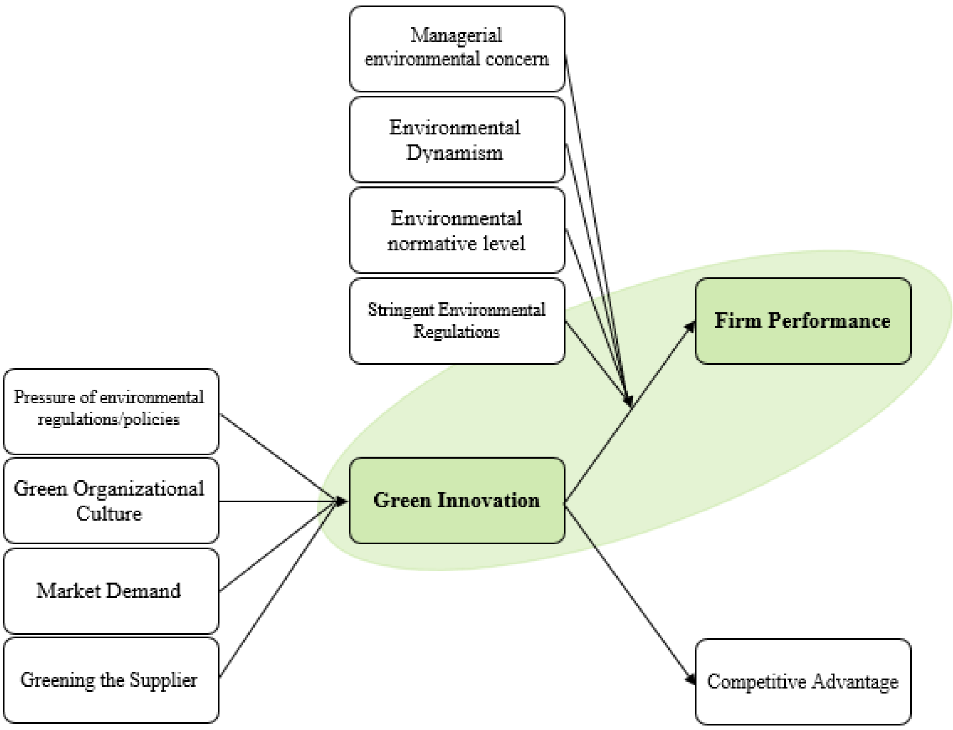

Figure I: Overview Scope of Field Green Innovative Studies. Gives an overview of the scope of field of the green innovative studies. The relationship shown in the green area represents the scope of this study.

	Items	Supporting Literature
Costs	Additional costs, such as the handling, storage and disposal of waste	Palmer et al., 1995; Porter & van der Linde, 1995; Olson, 2014; Kim et al., 2016
	Difficulty of developing sustainable green strategies to meet the demands of stakeholders	Kim et al., 2016
	Lower or negative influence on the performance of a firm if managers have incomplete information and limited time and attention	Chan et al., 2016; Dangelico, 2016
	New green innovations require start-up subsidies in order to compete with older non-green innovations	Olson, 2014
Benefits	Raises productivity and profitability, improves efficiency and reduces costs of investments	Chen et al., 2006; Hsu, 2009; Chiou et al., 2011;
	Lowers emissions	Russo & Fouts, 1997
	Higher quality of products or services	Chen et al., 2006
	Higher selling price	Porter & van der Linde, 1995; Russo & Fouts, 1997; Chen et al., 2006; Aguilera-Caracuel & Ortiz-de-Mandojana, 2013; Olson, 2014
	Improves market position	Schumpeter, 1934; Lin et al., 2013; Gürlek & Tuna, 2018
	Sustainable future	Lin et al., 2013
	Attracts new customers	Gürlek & Tuna, 2018
	Saves on operating costs by recycling and reusing materials	Hart, 1995; Chen et al., 2006; Chiou et al., 2011; Aguilera-Caracuel & Ortiz-de-Mandojana, 2013
	Acquires a better ecological reputation	Chen et al., 2006; Aguilera-Caracuel & Ortiz-de-Mandojana, 2013; Lin et al., 2013
	Differentiates product from competitors	Hart, 1995; Aguilera-Caracuel & Ortiz-de-Mandojana, 2013
	Prevents firms from facing environmental protests or penalties	Porter & van der Linde, 1995
	Protects the environment by reducing the negative impact on the environment during material acquisition, production, and delivery	Reinhardt, 1998; Klassen & Whybank, 1999; Chen et al., 2006; Oke et al., 2007
	First-mover advantage	Chen et al., 2006
	Gain competitive advantage	Hart, 1995; Porter & van der Linde, 1995; Chen et al., 2006; Ar, 2012; Tseng et al., 2013; Chang, 2016; Kim et al., 2016; Gürlek & Tuna, 2018
	Gain a better performance of the firm	Ar, 2012; Aguilera-Caracuel & Ortiz-de-Mandojana, 2013; Lin et al., 2013; Chan et al., 2016; Chang, 2016; Gürlek & Tuna, 2018

Table II: Overview of costs and benefits of Green Innovation. Gives an overview of the costs and benefits that have to do with green innovation with its supporting literature.

2.4 Hypothesis Development

In this section, the arguments used to explain the positive relationship between the types of green innovation and firm performance will be described.

It all started with the change in regulatory policies that affected firms. Although, it was understood that innovation could improve market position compared to competitors, create entry barriers, establish a leadership position, create new distribution channels and customers (li et al., 2010), many firms still saw green innovation as an obstacle towards a better financial future (Ar, 2012). Fortunately, previous studies did prove the opposite, namely that investing in green innovation does contribute towards a better world, but also a better performance of the firm. Ar (2012) finds that green product innovation encourages the use of raw materials efficiently and this results in lower costs and new ways of converting waste into saleable products. This could increase cash flow and thus increase the performance of a firm. Lin et al. (2013) agree and state that with this type of green innovation firms could gain sustainable development. Moreover, Chan et al. (2016) add that firms could use these regulations in their advantage by developing green innovations as it is a key capability for competitiveness that will increase the performance of a firm. Many firms that are unable to cope with the changing industries will not survive. Literature states that green innovation converts the increasing pressure of environmental regulation into a better performance of the firm. Something all firms have to deal with, so managers should have a proactive attitude towards it (Chen et al., 2006; Chiou et al., 2011; Chan et al., 2016; Chang et al., 2016).

Furthermore, Artz, Norman, Hatfield, and Cardinal (2010) state that firms being able to develop and exploit their innovative capabilities is known as one of the most critical determinants of firm performance. A continuous stream of innovations allows a firm to develop or maintain a better market position. So, a relatively rapid stream of innovations could enable a firm to constantly generate high profits. Choi and Williams (2013) describe three ways of how all kinds of innovation could impact firm performance. They firstly explain that technical knowledge is hard to imitate within a short period. So, the firm could have a competitive advantage in this period and therefore the firm could gain a better market position to see its sales increase. Secondly, firms that continuously use their technical knowledge and experience to create new opportunities within their competitive field will be more adaptable to changing environments and thus are more likely to identify profitable opportunities. And thirdly, this exceptional knowledge and experience could provide better resources that are necessarily for executing the profitable innovations.

Additionally, the theories already argue the positive impact of green innovation as Schumpeter (1934) explains that adaptable firms that try new creative ways of operating are more likely to outperform firms that do not, especially in a competitive environment. Green innovation is one of these creative ways nowadays, because in order to invest in green innovation a firm has to try new ways of using its knowledge, technology and resources. By using the capabilities of a firm and its valuable resources that are difficult to obtain and hard to imitate or trade a firm could gain a better performance of the firm. Therefore, the firm has to identify these potential key resources as it is a key driver of firm performance. Although the institutional theory describes that firms within the same environment will have similar institutionalized and legitimate practices and motives, it is expected that countries will regard and respond differently. Furthermore, looking at the three types of factors described by the contingency theory this study focuses on the direct relationship between the response factor and performance factor, because there are many contextual factors that could trigger a firm to innovate in way that also takes into account the environment. Of course, based on the factors described by the contingency theory, green innovation will be used as the response factor. Regarding the performance factor, as already stated, studies name firm performance instead of competitive advantage as the most important performance factor (Ar, 2012; Gürlek & Tuna, 2018).

So, empirical evidence regarding the relationship between green innovation and firm performance generally describe a positive and significant outcome. However, most of the green studies only focus on green product innovation, because this type of green innovation is the easiest to measure. Next to that, most of them use a survey to measure it. Therefore, this study will take into account all parts of green innovation and will use an unbalanced panel dataset to try to confirm the evidence of previous literature. The named arguments based on the empirical evidence and theories described in this chapter lead to the following hypotheses:

H1 Green innovation affects firm financial performance positively.

3 METHODOLOGY

3.1 Research Methods

Previous studies with similar hypotheses as this study are analyzed to determine which method to use. This section mentions the different methods that are used by others to test the impact of an independent/contextual factor on a dependent/performance factor. These methods are Structural Equation Modeling (SEM), the Ordinary Least Squares (OLS) regression analysis and the fixed/random effects model (FE/RE). OLS and a fixed/random effects model will be used in this study, although SEM seems more appropriate at first sight. This will be explained in paragraph 3.2, but first each method will be described in this section.

3.1.1 Structural Equation Modeling

Structural Equation Modeling (SEM) is a statistical technique for testing and estimating causal relations using a combination of statistical data and qualitative causal assumptions. It models causal relationships within their nomological net, takes measurement error into account at the item level, and shows an intuitive graphical representation of the theory. There are two SEM techniques, namely the covariance-based SEM and the variance based SEM. SEM has some requirements for data and samples that apply to both techniques. The data must be metric, quasi-metric and/or dichotomous. It is striking that most of the studies within the field of green innovation use SEM to test their hypotheses, because they gather their data by using surveys (Chen et al., 2006; Li et al., 2010; Chiou et al., 2011; Ar, 2012; Chan et al., 2016, Chang, 2016; Gürlek & Tuna, 2018). The Likert scales data used by these surveys are examples of quasi-metric and dummy variables are examples of dichotomous. One advantage of SEM is that there are no distributional assumptions, which means that data may be non-normal, skewed, and kurtotic. However, it does have requirements regarding sample size, because the recommended sample size is ten times the number of maximum arrowheads pointing on a latent variable. Also, technically, the number of observations could be smaller than the number of variables and the number of parameters. So, exceeding the recommended sample size makes convergence likely. But, this will be too small to even identify moderate effects (Henseler, 2017).

In SEM the model of the relationship between the variables will be displayed as shown in Figure II, where x stands for the indicators, also called the observed variables, ξ stands for the latent variable, the unobserved variable, ε stands for the error terms, λ stands for loading factors, and the arrow reflects a linear relationship. The latent variable in this study would be green innovation and examples of indicators are; using less or non-polluting/toxic materials, improving and designing environmentally friendly packaging for existing and new products, recovery of company's end-of-life products and recycling, using eco-labelling (Chiou et al., 2011; Ar 2012; Chan et al., 2016), low energy consumption during production/use/disposal, use of cleaner technology to make savings and prevent pollution (Chan et al., 2016).

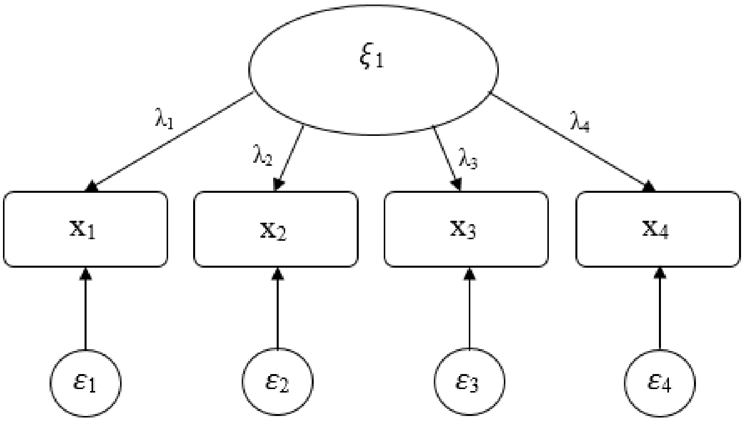

Figure II: a Structural Equation Model.

So, many studies with a similar hypothesis as the one used in this study use SEM to measure their model. Ar (2012), for example, uses SEM for testing the relationship between green product innovation and firm performance, because of the fact that SEM is designed to examine and test relationships and hypotheses among research constructs in order to identify latent variables in the conceptual model. Research constructs are variables that indicate the operationalisation of concepts and latent variables should correspond to these constructs. Latent variables are variables that cannot be observed directly. So, these variables are rather inferred from other directly observable variables. SEM has the ability to impute relationships between latent variables from observable variables. Next to that, SEM could also be used to determine directions and significance of the relationships. Chiou et al. (2011) also use SEM to test their hypotheses and therefore they had to identify the latent variables that are exogenous and endogenous. The first describes independent variables that are not influenced by other latent variables and the second describes dependent variables that are affected by exogenous variables in the model. Additively, Chan (2016) uses the same method to test their hypotheses and explains that it includes two consecutive levels of analysis, namely the measurement model and thereafter the structural model. These will now be explained.

3.1.1.1 Measurement Model

The measurement model contains an evaluation of the reliability and the validity. In this model the latent variables will be defined by using observable variables (Henseler, 2017). Chiou et al. (2011) add that the measurement model, next to evaluating the reliability and validity of the model, also defines relationships between the observed and unobserved variables.

Firstly, before analysing the two levels of analysis, the sample size must be taken into account. Chiou et al. (2011) state that sample size is one important issue in SEM, because it affects the degrees of freedom of the model and the model fitting process. A sample size must be between 100 and 200 and below 100 is not stable. When using a survey, one must also use a test to verify non-response bias between the groups of respondents. A *t*-test and Chi-Square test could be used as a test. The *t*-test evaluates the differences in means between two groups and the Chi-Square test examines the two groups based on control variables, such as industry level, firm size, and firm age. Insignificancy in these tests mean there are no significant differences between the two groups. So, when the sample size requirement is satisfied and the global fit indices of the measurement model are accepted, the measurement model could be examined.

So, thereafter, one could perform an exploratory or a confirmatory factor analysis and should check the global fit indices. A factor analysis itself is a method used to reduce a large number of variables into fewer factors. An exploratory factor analysis is a method to detect the underlying structure of a large set of variables. A confirmatory factor analysis is used to test how well the measured variables represent the number of constructs. So, it allows for the assessment of fit between observed data and an a priori conceptualized, theoretically grounded model (Hooper, Coughlan, & Mullen, 2008). Ar (2012), for example, started with an exploratory factor analysis to determine the measurement scales and thereafter a confirmatory factor analysis was conducted to validate the data. The latter is used to verify unidimensionality, discriminant and convergent validity. But, before testing unidimensionality, reliability and validity, Ar tests the global fit indices of his model. Regarding unidimensionality, he deleted items that loaded on multiple constructs and with too low item-to-construct loadings. In this way, it is possible to check whether the requirements arising from measurement issues are satisfied or not to start with SEM. Gürlek & Tuna (2018) also perform a confirmatory factory analysis and then test their structural model. To do this, they used the two-stage approach of Anderson and Gerbing (1988) wherein firstly the measurement model is examined separately from the structural equation model to test whether the measurement model has acceptable fit indices. Secondly, confirmatory factor analysis is performed. The maximum likelihood method was used to test the measurement model and structural model. However, one can only use this method if the assumption of normal distribution is achieved. Li et al. (2010) and Chang (2016) also use a confirmatory factor analyses for all constructs to further test the composite reliability and construct validity. Moreover, Chiou et al. (2011) used confirmatory factor analysis as a pre-test analysis to validate the sample size and non-response bias between the two groups. The first is of great importance, because it affects the degrees of freedom of the model and the model fitting process. So, firstly a confirmatory factor analysis must be performed to verify reliability and validity and to check the global fit indices of the measurement model.

So, these factor analyses are necessary to assess the reliability and validity of the reflective measurement models within this kind of research. Therefore, reliability and validity will be discussed in more detail. Reliability refers to the overall consistency of the model and validity refers to the extent that the model measures what is was designed to measure. Henseler (2017) describes two types of reliability, namely construct reliability and indicator reliability and two types of validity, namely discriminant validity and convergence validity. However, no study within this field of study mention any measure of indicator reliability, so that one will be left out. Examples of construct reliability are Dillon-Goldstein‘s rho, Dijkstra-Henseler‘s rho, and the most popular and therefore most used one is Cronbach’s alpha coefficient. Although, previous studies refer to the term composite reliability when they test construct reliability measures. These different types of reliability and validity will now be described.

Firstly, regarding construct or composite reliability, many studies use Cronbach’s alpha to test composite reliability of each construct and items established in their study (Chen et al., 2006; Oke et al., 2007; Li et al., 2010; Chiou et al., 2011; Ar, 2012; Lin et al., 2013; Chan et al., 2016; Chang, 2016; Gürlek & Tuna, 2018). The value is between 0.00 and 1.00 and the larger the value, the better is the consistency in the measurement (Vogt, 1999). Hair, Anderson, Tatham and Black (1998) state that the minimum requirement must be 0.70. Nunnally (1978) adds that in early phases of research, a value of 0.70 is regarded as acceptable. In later phases, the threshold should be higher, for instance 0.80 or 0.90. However, newer scales have a less strictly threshold, because the value must be higher than 0.60. Next to Cronbach's Alpha, Chiou et al. (2011) also used Corrected Item-Total Correlation (ITC). ITC sums up each item correlation and then excludes items with ITC values below 0.40. This makes it possible to check if excluding them increases the value of Cronbach’s alpha (Nunnally, 1978). Unfortunately, as already stated, no study mention any measure of indicator reliability.

So, secondly and thirdly, the validity will be tested. Chang (2016) describes three ways to verify the validity of the measurement model. Firstly, when a study uses a survey it must refer to previous research to design questionnaire items to achieve a high level of content validity. Thereafter, the study must measure the average variance extracted (AVE) to access the discriminant validity of the measurement model. Thirdly, the value of AVE of all constructs must be more than 0.5, so that the convergent validity is acceptable. The majority of studies use AVE to test for discriminant and convergent validity, which measures the internal consistency of the model (Li et al., 2010; Chiou et al., 2011; Ar, 2012; Chan et al., 2016; Chang, 2016; Gürlek & Tuna, 2018). Fornell and Larcker (1981) state that the value of AVE of each construct should exceed the squared correlation among other constructs in that model. Li et al. (2010) add that the value of AVE should be higher than 0.50 (Fornell & Larcker 1981; Henseler, 2017). Chan et al. (2016) and Chang (2016) also acknowledge that the AVE of each construct should be compared with the square of the correlation between all possible pairs of constructs to test for discriminant validity. Discriminant validity is acceptable if the AVE values are greater than the square of the correlation between all possible pairs of constructs. Li et al. (2010) take a different approach and use Chi-square difference for all constructs in pairs to assess the discriminant validity of the measures. They take their two moderator variables as two variances and together to see if the two moderator variables should be used as two separate factors or one combined factor. They also used an *F*-test to check whether there is an increment in R^2 and used the variance inflation factor (VIF) of the regression model to check whether the condition of no collinearity is met. Chen et al. (2006) agree and also use the VIF value.

Lastly, after checking for reliability and validity, one must also take into account the possibility of common method bias when the study relies upon the assessments of respondents to conduct the measures of variables (Li et al., 2010). Chan et al. (2016) also check for the impact of common method variance by using Harman's single factor test and the lowest bi-variate correlation among the manifest variable as the marker variable. For this the adjusted correlation matrix must be composed and must be tested with the significance of the adjusted correlations. Common method bias does not exist when the correlations are still significant after the adjustments and when the reliability and validity tests are acceptable.

3.1.1.2 Structural Model

The structural model contains explanatory power and the assessment of effects wherein the validation of the measurement models is a requirement for assessing the structural model. This model shows potential causal dependencies between endogenous and exogenous variables (Henseler, 2017). This second level of analysis defines the relationships among the unobserved variables and tests the hypotheses of the research (Chiou et al., 2011).

If the measurement model is acceptable, the structural model could be tested wherein the good fit of the measurement model is tested first. Chiou et al. (2011) carry out the goodness of fit test and used different indices to negate bias related to the use of a single index. Therefore, they used the goodness of fit index (GFI), Chi-Square (χ^2)/degrees of freedom (df), the comparative fit index (CFI), the Tucker Lewis index (TLI), the normed fit index (NFI) and the incremental fit index (IFI). A value of 0.90 is acceptable for the GFI, CFI, TLI, NFI and IFI tests and GFI and AGFI is acceptable between 0.80 and 0.89 (Hu & Bentler, 1999). χ^2/df must be below 3.0, but this measure is only used when the sample size is limited and therefore it replaces Chi-Square (χ^2). So, a final structural model could still be acceptable if the values of all these tests are acceptable, even if the sample size is limited.

Chan et al. (2016) also test the good fit of the model by using χ^2, CFI, TLI. Additively, they also check for the root mean square error of approximation (RMSEA) and (SRMR). RMSEA avoids issues of sample size, because it analyses the discrepancy between the hypothesized model and the population covariance matrix. The value is between 0 and 1 and the lower the better model fit. SRMR is an absolute measure of fit and is the standardized difference between the observed and predicted correlation. A value of 0 means a perfect fit, but a value of less than 0.08 is acceptable (Hu & Bentler, 1999). Chang (2016) uses GFI, NFI, CFI and RMSEA to test for the good fit of the model.

When the good fit of the model is accepted, the hypotheses could be tested. The hypotheses are supported when the path coefficients between the constructs are significant and show the hypothesized sign (Henseler, 2017).

3.1.2 Ordinary Least Squares regression analysis

Ordinary Least Squares (OLS) regression analysis is an econometric methodology used to estimate the unknown parameters in a linear regression model. Least squares means that the analysis minimizes the sum of the squares of the differences between observed and predicted dependent variables. The OLS regression analysis is consistent when the independent variables are exogenous, meaning that the independent variable is not being influenced within the model. Furthermore, OLS regression analysis is most efficient when errors are normally distributed and are not heteroscedastic and autocorrelated. When the OLS estimator is normally distributed, it is similar to the maximum likelihood estimator. Furthermore, the regression analysis has two hypothesis that will be tested. The first one tests whether the estimated regression is better than just predicting that all values of the dependent variable equal its sample mean. The null hypothesis states that there is no explanatory value of the estimated regression. The alternative hypothesis states that the regression does have explanatory power. An *F*-test is used to test the sign and significance of the regression. The second one tests whether its estimated coefficient differs from zero. The null hypothesis states that the true coefficient is zero and the alternative hypothesis states otherwise, meaning that the variable does have explanatory power. A *T*-statistic is used to test the sign and significance of the regression (Goldberger, 1964).

Moreover, the OLS regression analysis has some assumptions it has to fulfil in order to produce the best estimates of the coefficients. Firstly, the errors in the regression must have a conditional expected value of zero, because in this way the OLS regression is exogenous and thus the independent variables are as well. The independent variables are endogenous when this assumption is not met. A solution to this problem is to perform an Instrumental Variables (IV) regression analysis. This test is used to control for confounding and measurement errors (Hayashi, 2000). Next to the OLS regression analysis, Chen, Leung and Evans (2018) perform this IV regression to extract the exogenous component of their independent variable and this helps explaining the outcomes of innovation. Their results conclude that the magnitudes of the IV estimates are larger than those of the OLS regression analysis, however both are positive and significant. So, this suggests that the OLS regression analysis may have some bias of omitted variables. Huang and Hou (2019) also thought of using the IV regression analysis to examine the marginal effect of innovative activities on the profitability of a firm, because of the endogenous causality that exists between a firm's innovative activities and its profitability. They used the Wu-Hausman test to analyse this problem and identify no endogeneity. Therefore, they use the fixed effects regression model, but more about this model later. However, if the endogeneity problem was indeed identified, they would have used the panel IV technique.

Secondly, the independent and control variables must all be linearly independent. There does not exist linear dependence if this is the case. But, if this does exist, then the independent and/or control variables are multicollinear. For instance, Abuhommous (2017) tests whether investment in trade credit is positively related with firm's profitability. This kind of relationship is similar to the one used in this study, only he studies trade credit. He uses panel data, controls for unobservable heterogeneity and performs a regression to test their hypothesis. He describes that their correlation matrix does not show any high correlation between the independent variables, so he concludes that multicollinearity does not exist. Pramod, Krishnan and Puja (2012), Gui-long, Yi, Kai-hua and Jiang (2017) and Zhou and Sadeghi (2019) also state that the Pearson correlation matrix could be used to see if there exists multicolinearity among the regressors. Vithessonthi and Racela (2016) analyze the correlation coefficients between key variables before performing the OLS regression analysis as well. Multicollinearity will not be a great problem when the correlation coefficients between the explanatory variables are below 0.30. But, when the correlation coefficient between two measures is above 0.30 and statistically significant, the variables will be added separately in the regressions. Next to that, Ehie & Olibe (2010) test the influence of R&D investment on the market value of a firm. They have a pooled cross-sectional sample and use the OLS regression analysis to test this. But, before performing this analysis, they also test for multicollinearity by examining the VIF values of the independent variables as well. Moreover, Li et al. (2010) mean-centered all the variables to minimize the threat of multicollinearity.

Thirdly, there must not be any spherical errors. Splitting this into two parts, the data must not be heteroscedastic and there must not exists autocorrelation. To test for heteroscedasticity, one can perform White's Heteroscedasticity-Consistent Standard Errors and Covariance method. The study of Pramod et al. (2012), Ortega-Argilés, Piva, Potters and Vivarelli (2009), Ortega-Argilés et al. (2011) and Aggelopoulos, Eriotis, Georgopoulos, and Tsamis (2016) are one of many that corrected their OLS panel data model for potential heteroscedasticity by using the White's method. Anagnostopoulou and Levis (2008) have a balanced panel dataset and used the OLS regression method to test the impact of R&D on firm performance and also use White's heteroscedasticity robust standard errors to correct their OLS panel data for heteroscedasiticity. Moreover, Aggelopoulos et al. (2016) also tested the stationarity of the panel by performing a Fisher unit-root test. The ideal outcome of this test is to be able to reject the null hypothesis of non-stationarity at the 1% level for both dependent and independent variables. Next to that, they also run a basis *F*-test for joint parameter insignificance. Here the outcome must be to be able to reject the null hypothesis that coefficients are jointly insignificant at the 1% level. This ensures the robustness of the OLS panel data model. However, when the presence of heteroscedasticity exists, a solution would be to perform a Weighted Least Squares (WLS) regression analysis instead of an OLS regression analysis. For example, Chen, Lai and Chang (2017) investigate the long-term stock market performance of firms following announcements of new product introductions and they use Carhart's four-factor model to test this (Carhart, 1997). Within this model they use the OLS regression analysis and the weighted-least-square (WLS) regression analysis to correct for misevaluations of abnormal returns, also called event-bunching bias. Their results show the same sign and significance, but stronger in the WLS regression analysis.

Furthermore, there exist no autocorrelation when the errors are uncorrelated between the observations. One benefit of using panel data, like this study, is the fact that this assumption may be violated. Aggelopoulos et al. (2016) hypothesize whether R&D investment is likely to have a positive effect on operating performance of SMEs in a small open economy. They perform an OLS regression using panel data for their sample period and describe that it can provide more information on the variability and efficiency as an advantage of using panel data over conventional cross sectional and time series data. Next, Gui-long et al. (2017) have a novel unbalanced panel data set. They construct a longitudinal sample consisting of time series cross-sectional data. The reasons for this are that it prevents bias caused by unobserved heterogeneity and it may reveal dynamics that are difficult for simple cross-sectional data to detect. The difference between panel data and cross-sectional or time series data is that panel data usually have significantly more observations and panel data also decreases the multicollinearity between variables, which improves the estimates. However, when there is autocorrelation, it is better to use a Generalized Least Squares (GLS) regression analysis as this analysis is more efficient than OLS and WLS when there is a certain degree of correlation between the residuals. For example, Andras and Srinivasan (2003) hypothesize whether advertising intensity and/or R&D intensity of the firm are positively related to the profit margin of the firm. They use an OLS regression analysis to test this relationship. However, their OLS regression revealed that errors have a higher variance at higher levels of R&D intensity. Therefore, they also use a GLS regression analysis with the inverse of R&D intensity as the weighting factor. In this way they could correct for heteroscedasticity.

Fourthly, although it is not needed for the validity of the OLS regression analysis, the errors terms must have a normal distribution. This does not apply to the dependent variable. And fifthly, when using cross-sectional data, the observations must also be independent and identically distributed. Meaning that all observations are taken from a random sample. Cross-sectional data is a type of data that is collected through the observation of many subjects at the one point or period of time. The difference between cross-sectional data and time series data is that time series data is a set of observations collected at usually discrete and equally spaced time intervals and not at one point or period of time. Another type of data, panel/longitudinal data, is a combination of these two and looks at how the subjects change over a time series (Goldberger, 1964).

Moreover, the general equation of the OLS regression analysis will be described in order to better understand this analysis. The multiple linear model equation for the OLS regression analysis is described to predict the value of the dependent variable:

$$Y_{i,t} = \beta_1 X_{i,t,1} + \beta_2 X_{i,t,2} + \ldots + \varepsilon_{i,t}$$

where $Y_{i,t}$ represents the dependent variable, X represents the independent variables, β represents the regression coefficient of the independent variables for firm *i* at time *t* and ε represents the unobserved random errors that could have an influence on the dependent variable. In these kind of models a lag is also possible, meaning that variables could be measured at different times. For example, a variable measured three years before the other variables will be indicated by *t - 3*.

Many studies use the OLS regression analysis to test their independent variable on their performance variable (Andras & Srinivasan, 2003; Chen et al., 2006; Anagnostopoulou & Levis, 2008; Kale, Reis, & Venkateswaran, 2009; Loughran & Shive, 2011; Feeny & Rogers, 2013; Lin et al., 2013; Ilyukhin, 2015; Aggelopoulos et al., 2016; Frijns, Dodd, & Cimerova, 2016; Abuhommous, 2017; Zhou & Sadeghi, 2019). For example, Vithessonthi and Racela (2016) hypothesize whether R&D intensity and the level of internationalization of a firm has a negative effect on operating performance and a positive effect on firm value and perform an OLS regression analysis. They also include firm-fixed in their panel OLS regressions in order to control for unobservable time invariant firm-specific effects and include period-fixed effects in order to control for unobservable time-varying macro-level effects. Chen et al. (2006) use the regression analysis to test the relationship between green product innovation and corporate competitive advantage. Lin et al. (2013) also use it to test whether market demand is positively associated with green product innovation performance, whether green product innovation performance is positively associated with firm performance, and whether market demand is positively associated with firm performance.

3.1.3 Fixed/random effects model

Next, some studies use a combination of the OLS regression analysis with a fixed/random effects model analysis. Pramod et al. (2012), for example, test the R&D intensity and market valuation of a firm with an unbalanced panel dataset. They begin with the pooled OLS regression method. However, they mention that when using the OLS regression method one ignores the panel structure of the data. The OLS regression method assumes that observations are serially uncorrelated and that the errors across individual and time are homoskedastic. This is not always the case. The estimates of OLS are consistent, but inefficient when these errors are not homoskedastic. Next to that, omitted variable bias could also be present. That is why they also use another regression, namely fixed/random effects regression analysis. Ortega-Argilés et al. (2011) investigate the relationship between R&D expenditures and the productivity of a firm and use an unbalanced longitudinal dataset. They agree with the method of Pramod et al. (2012) and used OLS regression analysis and fixed/random effects models as well to test their relationship. In this way, they are able to control for possible idiosyncratic sectoral effects. Kumbhakar, Ortega-Argilés, Potters, Vivarelli and Voigt (2011) investigate the impact of corporate R&D activities on firm performance and used an unbalanced longitudinal dataset. They state that choosing the most appropriate parametric or non-parametric method is a judgment call, because both have strengths and limitations. They also use the OLS regression analysis method and a random effects panel model to test their hypothesis.

The two models are both statistical models, but for the fixed effects model the parameters are non-random quantities and in a random fixed effects model they all or some are, of course, random. Furthermore, in a fixed effects model the group means are fixed and in a random effects model the group means are a random sample of a population. The random effects model is a special case of the fixed effects model and these models control for unobserved heterogeneity when it is constant over time and not correlated with independent variables. Panel data could be estimated using either random or fixed effects model. So, random effects includes between effects and this explores cross-sectional dimension by using the firm means over time. Fixed effects includes within effects and here the focus is on time series data (Greene, 2011).

Both models have assumptions. The assumption regarding the fixed effects model states that individual-specific effects must be correlated with the independent variables. The random effects model assumption states that the individual specific effects are uncorrelated with the independent variables. One could use the Durbin-Wu-Hausman test, also called the Hausman test, to test this assumption. The test checks if there is a correlation between the unique errors and the regressors in the model, wherein the null hypothesis states that there is no correlation. If the null hypothesis is accepted, one could use either fixed or random effects model, because both will be consistent. However, only the random effects model will be efficient. If the null hypothesis is rejected, the fixed effects model will be consistent and the random effects model would not. Ortega-Argilés et al. (2009) name various reasons why to choose the random effects model over the fixed effects model. Firstly, the nature of their unbalanced short panel dataset affects the within-firm variability component of the data. Secondly, it is better to use the random effects model when the within-firm component of the variability of the dependent variable turns out to be overwhelmed by the between-firms component. Lastly, in the fixed effects model it is not possible to estimate the coefficient of any time-invariant regressor, because it is absorbed into the individual-specific effect. But, of course, the outcome of the Hausman test must also be taken into consideration. Furthermore, a large test statistic of the Hausman test could also indicate errors-in-variables (EIV) or that the model used is misspecified (Gardiner, 2009; Green, 2011).

Again, to better understand the model, the general equation of both fixed and random effects will be described. The equation for the fixed effect model is written as:

$$Y_{i,t} = \beta_1 X_{i,t,1} + A_{i,t} + U_{i,t}$$

where Y represents the dependent variable, X represents the independent variables, β represents the regression coefficient of the independent variables, A the unknown intercept for firm *i* at time *t* and *U* the error term.

Furthermore, the equation for the random effects model is written as:

$$Y_{i,t} = \beta_1 X_{i,t,1} + A_{i,t} + U_{i,t} + \mathrm{E}_{i,t}$$

where Y represents the dependent variable, X represents the independent variables, β represents the regression coefficient of the independent variables, A the unknown intercept for firm *i* at time *t*, *U* the between-effects (random effects) and E the within-effects. In this model the variables could be measured at different times as well.

Many studies use a fixed or random effects model for testing their relationship between an independent variable and a performance factor. For example, Loughran and Shive (2011) test the impact of venture capital investments on public firm stock performance and use panel data. They perform a fixed-effects model. The advantage of using this type of regression is that it allows industry effects. Pramod et al. (2012) also use a fixed/random effects model. Panel data could be estimated using either random or fixed effects model. Random effects includes between effects and this explores cross-sectional dimension by using the firm means over time. Fixed effects includes within effects and here the focus is on time series data. As the theory describes, they use the Hausman specification test to check which one to choose over the other. Moreover, Ilyukhin (2015) tests the relationship between financial leverage and firm performance, but have an unbalanced panel dataset. An unbalanced panel dataset means that a part of the firms does not have observations for the whole period of study. Therefore, they use the fixed effects.

Huang and Hou (2019) state that many studies investigated the relationship between firm innovation and firm profitability, wherein the direction of causality runs from innovation to profitability. This is because of the perception that firms invest in R&D to continue growing through product development and to stay competitive. They use an unbalanced panel dataset to study the causal relationship between firm profitability and innovative activities and analysed the determinants of firm profitability. They used Granger causality to examine the direction between firm profitability and innovative activities. The null hypothesis states that a firm's innovative activities does not Granger-cause firm profitability. After that, they used both random effect and fixed effect panel data models. However, they state that they choose fixed effects estimators over random effects estimators, but they did not know whether they could assume that the individual effect was uncorrelated with other explanatory variables. They did use the Hausman test to explore which model to use, but the problem that goes with this is the endogenous causality between a firm's innovative activities and the firm profitability. Therefore, they used GMM regression analysis. This is the most used method when panels have small *T*-value and large *N*-values. The results indicate that there is a one-way causality from a firm's innovative activities to its profitability. However, they also find some weak evidence regarding the direction of causality from a firm's profitability to its innovative activities.

3.2 Model used in this study

As stated, the majority of studies within the field of green innovation choose SEM as their method. So, it seems logical to use this model as well. However, all these studies use a survey to gather their data, because green innovation is difficult to measure. Unfortunately, this implies that green innovation is not directly observable and thus a latent variable. SEM is one of most obvious methods to use for testing relationships when one only has latent variables. However, in this study an unbalanced panel dataset will be used. Therefore, looking at the studies with a similar relationship between an independent variable and a performance factor, it is more appropriate to use OLS regression. Although performing a fixed/random effects model could also be possible.

The hypothesis posits that green innovation positively influences firm performance. To test if this is indeed the case, the following OLS regression estimation will be run.

$$PERF_{i,t} = \beta_1 (GI)_{i,t-3} + \beta_2 (SIZE)_{i,t} + \beta_3 (AGE)_{i,t} + \beta_4 (LEV)_{i,t} + \beta_5 (IND)_{i,t} + \beta_6 (COU)_{i,t} + \varepsilon_{i,t}.$$

Where $PERF_{i,t}$ represents the different measures of firm performance, namely ROA, ROE, ROS, and Profit Margin. $GI_{i,t-3}$ represents the independent variable Green Innovation, measured by the number of patents and citations for a 3-year time lag. Meaning that a patent granted in

2010 shows its impact in 2013. It happens more often that a lag is used in the analysis and many still argue about how many years this lag must be (Artz et al., 2010). However, based on previous literature, this study will use a 3-year lag and this will be described in paragraph 3.3.2. Furthermore, $SIZE_{i,t}$ represents the control variable firm size, $AGE_{i,t}$ represents the control variable firm age, $LEV_{i,t}$ represents the control variable firm leverage, $IND_{i,t}$ represents the dummy variable industry control, and $COU_{i,t}$ represents the dummy variable country control. Furthermore, β_1 represents the regression coefficient of the independent variable for firm *i* at time *t* and ε represents the unobserved random errors that could have an influence on firm performance.

A variety of models will be constructed on the different measures of the dependent variables with the execution of the OLS regression analysis. In order to establish a benchmark, the first model will only consists of all control variables and the independent variables will be left out. Thereafter, different combinations of variables will tested and lastly the full model will be tested. In this way, one could find changes in variability when the measures of green innovation are added to the model. So, the impact of green innovation will then become clear and this will be done for all the performance measures separately. The variables will be tested for the alpha significance level of 10%, 5%, and 1%.

Moreover, this study has an unbalanced panel dataset, because using a balanced dataset would have the consequence of not having enough observations. So, an unbalanced dataset brings more observations and thus the sample will be larger. This could cause some bias, because some firms could be represented more in the sample and this is not favourable when using the OLS regression analysis. In panel data the behaviour of entities are observed across time. Examples of these entities are companies, countries or individuals. Panel data allows to control for unobservable variables across firms or variables that change over time but not across entities. Panel data is much more informative than either cross-sectional or time series data, but the problem that could arise is that one may find insufficient observations for a particular period of time. For example, firms could have 50 granted green patents in year 2010 and only 20 granted green patents in 2011, but still have a higher firm performance in 2014 compared to 2013. The 50 granted green patents could still have an influence on the firm performance of 2014, while the analysis only looks at the 20 granted green patents, because of the time lag of 3-years. This problem could be prevented by performing a fixed/random effects model as a robustness check (Vithessonthi & Racela, 2016; Chen et al., 2018). Therefore, a fixed/random effects model will be used as such a check. This is in line with the study of Pramod et al. (2012) who describe that omitted variable bias could be present when using the OLS regression analysis. Ortega-Argilés et al. (2011) also perform both the OLS regression analysis and the fixed/random effects model, because it checks for individual firms' unobservables.

Studies also perform other robustness checks to strengthen their results. For example, Vithessonthi and Racela (2016) divide their sample into low and high based on the cross-sectional median value of R&D intensity as a robustness check. The dummy variable takes a value of 1 for innovations larger than the cross-sectional median, and zero otherwise. Subsequently, they divide their sample into small and large firms based on the cross-sectional median value of firm size. Again, the dummy variable takes a value of one for an observation with a firm size larger than the median, and zero otherwise. Loughran and Shive (2011) also split their sample, but into small, medium, and large firms. They also make sure the test is not driven by one industry or an omitted industry-level variable. For this, they use an individual industry-level OLS regression test on the five largest industries within their study. Furthermore, Vithessonthi and Racela (2016) use an alternative proxy for their independent variable. In this study citation count will used as a second measure of green innovation and not just as a robustness check. This will be explained in paragraph 3.3.2.

The robustness checks that will be performed in this study are a fixed/random effects model for the full sample, and extra OLS regression checks for: the full sample split by the median of size, a 2-year lag sample, a sample consisting of firms operating only in patent-sensitive industries, a sample consisting of firms with at least one citation, a 2010-2014 sample with using a 2-year and 3-year lag for firm performance improvement as the replacement of the dependent variable, and a sample using a citation dummy as the replacement of the number of citations.

3.3 Variables

3.3.1 Dependent variables

Based on previous literature and regarding the hypothesis, this study will use different measures of firm performance as the dependent variable. The literature is divided when it comes to the measurement of firm performance. Firm performance measures can be divided into accounting performance measures, such as Return On Assets (ROA), Return On Equity (ROE) and Return On Sales (ROS), market performance measures, such as stock returns, and hybrid performance measures, such as Tobin's Q.

There are a couple of measures that are used in most studies. These measures of firm performance are; ROA[5], ROE[6], ROS[7], Tobin's Q[8], and Profit Margin[9]. Other less frequently used measurements of firm performance are; Revenue Growth (Anagnostopoulou & Levis, 2008; Aggelopoulos et al., 2016), Gross Income (Anagnostopoulou & Levis, 2008), Total Revenue (Kober et al., 2012), Return On Capital Employed (ROCE) (Sridharan & Joshi, 2018), percentage of EBITDA (Sridharan & Joshi, 2018), Annual Stock Returns (Vithessonthi & Racela, 2016). In the context of this study, the most used performance measures will be described briefly.

Firstly, ROA is almost always used as a measure of firm performance, because it indicates the efficiency of a firm in managing its assets and thus a higher ROA means a better utilization of its assets (Sridharan & Joshi, 2018). It captures the ability of a firm to develop profits from its assets or investment base (Artz et al. 2010). Vithessonthi and Racela (2016) and Abuhommous (2017) measure ROA as the ratio of earnings before interest and taxes (EBIT) over total assets. Kale et al. (2009), Santos et al. (2014), Ilyukhin (2015), and Kim et al. (2016) measure ROA by net income divided by total assets. Frijns et al. (2016) measure ROA as operating income divided by the book value of total assets. Sridharan and Joshi (2018) measure it as the percentage of operating profits over total assets.

Secondly, ROE measures the ability of a firm to generate profits from its shareholders investments in the company. Kale et al. (2009), Santos et al. (2014), and Ilyukhin (2015) measure ROE as the ratio of net income to the book value of equity. Kober et al. (2012) describes that ROE is an adjusted measure that controls for the size of the firm. Next to using ROE, they also use Average ROE. This measurement is over the 4-year period for which they had data. Ibhagui and Olokoyo (2018) measure it as the ratio of EBIT to the book value of equity.

Thirdly, Santos et al. (2014) measure ROS as the ratio of net income to total sales. Vithessonthi and Racela (2016) measure it as EBIT to net sales and Gui-long et al. (2017) measure it as EBIT to total sales. Vithessonthi and Racela (2016) argue that ROS has an

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[5] Supporting literature: Kale et al., 2009; Artz et al., 2010; Aguilera-Caracuel & Ortiz-de-Mandojana, 2013; Choi & Williams, 2013; Santos et al., 2014; Ilyukhin, 2015; Chan et al., 2016; Frijns et al., 2016; Kim et al., 2016; Vithessonthi & Racela, 2016; Abuhommous, 2017; Gui-long et al., 2017; Ibhagui & Olokoyo, 2018; Sridharan & Joshi, 2018

[6] Supporting literature: Kale et al., 2009; Kober et al., 2012; Santos et al., 2014; Ilyukhin, 2015; Chan et al., 2016; Ibhagui & Olokoyo, 2018

[7] Supporting literature: Santos et al., 2014; Vithessonthi & Racela, 2016; Gui-long et al., 2017

[8] Supporting literature: Kale et al., 2009; Belderbos et al., 2010; Pramod et al., 2012; Ilyukhin, 2015; Frijns et al., 2016; Ibhagui & Olokoyo, 2018

[9] Supporting literature: Andras & Srinivasan, 2003; Ilyukhin, 2015; Aggelopoulos et al., 2016; Chan et al., 2016

advantage over ROA, namely that it avoids the effects of different assets valuations that are a result from the timing of investments or depreciation. They use ROS to replace ROA to test the robustness of their results. However, the results indicate that the two measures of firm performance do not perfectly substitute each other. Although many think operating margin and ROS are the same, they are not. The differences lies in the numerator of their formulas. For operating profit margin this is operating income and for ROS this is EBIT. The denominator for both is net sales. Moreover, Oke et al. (2007) describe that the amount of sales generated from innovations or new products is the most common measure of business performance. However, this study did not use ROA and ROE, because of the difficulty linking them to innovation (Griffin, 1997). Although they did not use ROS, they did use Sales Turnover and Net Profit Growth Before Tax. Furthermore, Choi and Williams (2013) name their choice of performance measures a limitation of their study and therefore recommend to use ROS as an alternative performance measure.

Fourthly, Tobin's Q estimates whether a firm is overvalued or undervalued and is also often used as a measure of firm performance. Kale et al. (2009) measure Tobin's Q as the ratio of the sum of market value of equity and the book value of debt to total assets. Frijns et al. (2016) measure Tobin's Q as the book value of total assets minus the book value of equity and the market value of equity, and divide it by the book value of total assets. Vithessonthi and Racela (2016) measure it as the ratio of the sum of the market value of equity and the book value of total debt to the book value of total assets. Ilyukhin (2015) measures Tobin's Q as a ratio of firm market capitalization to total assets. However, they describe that a stock price is needed to calculate this measure. This means only countries with well-developed stock markets are applicable. Furthermore, Pramod et al. (2012) state that Tobin's Q has been used the most to measure the market valuation and market performances of a firm, because it serves as a proxy for firm's value from an investor's perspective. They measure it as the ratio between the market value of firm's financial claims and the replacement value of assets, where an outcome higher than 1 means that the firm has better investment opportunities, growth potential and that indicates better management which leads to better market performance. However, they also name some limitations for using Tobin's Q. Agreeing with Ilyukhin (2015) they state that the market valuation data in undeveloped countries could be unreliable. Replacing it by the cost of the capital stock could lead to measurement errors. Therefore, many studies replace market value by the book value of debt and the book value of assets.

Fifthly, Andras and Srinivasan (2003) state that profit margin is one of the best available indicators of the ability of a firm to generate superior rate of return during future periods.

Therefore, it is expected to have a positive influence on the performance of a firm. They measure it as the ratio of profit after tax divided by net sales. Chan et al. (2016) agree with the substantiation and measure it as EBIT divided by operating income.

Furthermore, many studies within the field of green innovation use firm performance as their performance factor. For example, Ar (2012) follows the study of Eiadat, Kelly, Roche and Eyadat (2008) for measuring firm performance. They operationalize firms' business performance in terms of sales growth, market share, and return on investment. Lin et al. (2013) follow the study of Li et al. (2010) regarding the measurement of firm performance. Li et al. (2010) uses four items about a firm's relative performance against its main competitors, namely: market position, sales volume, profit rate, and reputation. However, because they use a survey, they use a seven-point Likert scale as measurement. Chan et al. (2016) also follow previous literature (Epstein & Staw, 2000; Kaynak & Hartley, 2008) to measure firm performance. Profit/loss, ROA, profit margin, and ROE are their four measures of firm performance. Aguilera-Caracuel and Ortiz-de-Mandojana (2013) measure firm performance by calculating ROA as well. They also looked at the improvement of firm performance, so therefore they used the change in ROA with the basis year as indicator. This means the change after 3 years was calculated as: (ROA year 3 – ROA year 0) × 100%.

In this study, firm performance will be measured using four proxies, namely the calculation of ROA, ROE, ROS, and Profit Margin. ROA is EBIT divided the book value of total assets. ROE is measured as the ratio of net income to equity. ROS is measures as EBIT divided by net sales and Profit Margin is measured as EBIT divided by operating income.

3.3.2 Independent variables

In this study green innovation will be used as the independent variable. Huang and Hou (2019) mention that innovation is one of the main activities that causes economic growth and industrial evolution. Feeny and Rogers (2003) state that measuring innovative activity is almost impossible, because the innovativeness of each firm will reflect a set of factors including knowledge, skills of employees, management methods, culture and networks. Although, for analytical work, many studies measure innovative activities by using innovation inputs (R&D expenditure) and outputs (patent applications) (DeCarolis & Deeds, 1999). Firms with successful R&D strategies and patent rights could profit from their patented products. Artz et al. (2010) state that the suitability of an innovation is determined by the effectiveness of legal protection mechanisms like patents. Firms seek patents in order to delay the ability of competitors to imitate their innovation, so that they could enjoy profits for a longer period of time. However, this all only continues until competitors catch up or when the government adjusts its regulations. So, the continuous improvements of products or technologies could enable firms to improve the position in the market and this could lead to an increase in profits and thus a better performance of their firm. Thus, literature of innovation divides innovation into innovation input and innovation output, and use two main measures to measure these parts, namely R&D investments and the number of patents/citations (Artz et al., 2010; Choi & Williams, 2013). R&D investments or expenditures are assigned to innovation input, whereas the number of patents/citations are assigned to innovation output. These will now be substantiated.

R&D expenditures are associated with internal research capabilities, which enables a firm to create, understand, and use knowledge. These R&D expenditures are investments that contribute to the knowledge of a firm. Moreover, next to the creation of internal knowledge, R&D also allows evaluation of potential outcomes of the knowledge created (Hall, Griliches, & Hausman, 1986). Firms use their R&D activities to create innovations that will lead to new product and thus hopefully to a better firm performance.

However, not all innovations turn out to be successful, even though the firm has great technological and inventive potential. Santos et al. (2014) name using innovation input variables instead of output variables an important limitation to their study. Investors and firms must overcome the critical examination of the patent office, but must also take into account the economic feasibility of that patent. Meaning that the performance of the firm greatly depends on the cash flow of the patent, which makes patents a better measure of innovation than R&D investments or expenditures as they correlate better.

For the same reason, Artz et al. (2010) test the relationship between R&D spending and product announcements, which is a proxy for innovation and find that this relationship is not significant related. R&D relates to inventions and innovation. However, firms are more likely to patent inventions that could be commercially exploited than those that could not. So, they name the number of patents as a more reliable measure than R&D expenditures and also test whether patents are related to product announcements. They indeed find a significant relationship. Chen et al. (2018) acknowledge this and also state that the innovation input measure does not take into account the quality of the measure. So, they use the innovation output to capture the effectiveness of the utilization of the innovation as well and they measure it as the count of patents and citations.

The first measure of innovation output is the number of patent applications a firm filed in a year that are eventually granted. DeCarolis & Deeds (1999) name patents as representatives of stocks of organizational knowledge as patents are physical, codifiable manifestations of innovative ideas, techniques, and products that embody the knowledge of one or more employees of the firm. An innovation is patented if the net benefits of doing so exceed the costs. These costs can include the tangible costs of filing and defending patents, or the less tangible costs of information disclosure associated with patenting (Arora, Ceccagnoli, & Cohen, 2008). Many inventions ultimately result in marketable innovations, because patents ensure protection (Artz et al., 2010). However, DeCarolis and Deeds (1999) also name limitations to simply using patent count. First, simple patent count do not reflect the value of knowledge, which is better captured by citations. Second, firms tend to differ in their policies toward patents as some firms patent more than other firms. The estimated minimum costs of an issued patent are $ 12,000. This is small for a big firm, but big for a small firm.

So, next to the number of patents, the number of citations will also be used in this study. Griliches, Pakes and Hall (1986) use this second measure to capture innovation productivity, because the patent count vary in their technological and economic importance and therefore are not sufficient enough to capture innovation productivity. This second measure assesses the importance of a patent, because it is related to the social and economic value that is created by the innovation (Hall, Jaffe, & Trajtenberg, 2005). Citation count is measured as the total number of non-self citations ultimately received by the patents applied for in a given year. Thus, citations are how many times a firm's patents are cited by subsequent issued patents (DeCarolis & Deeds, 1999). Meaning that others want to use that specific document for further research purposes. So, green innovation will be based on the intensity of green innovations and it will be calculated by the total number of patents that could be attributed to green patents (Melvin, 2002; Harhoff & Wagner, 2009) and citation count (Hall et al., 2005).

Other studies also use at least one of the innovations measures described above. Frietsch and Grupp (2006), for example, named patents as the most important proxy to define innovation. Zhou & Sadeghi (2019) agree and also mention that patents are an output of innovation capital during the process of the production of a firm. Therefore, they use the natural logarithm of the number of patent applications and acquired patents as well to define innovation. Czarnitzki and Kraft (2012) use both R&D investments and patent count as a measure of innovation to test the impact on firm performance and their results conclude that patents have a more significant impact on firm performance than R&D investments. Choi & Williams acknowledge the inputs and outputs of innovation and also use R&D intensity and patent intensity as their independent variables. However, they find that R&D intensity is not statistically significant for both their two firm performance measures. For ROA it even shows a negative sign. On the other hand, patent intensity does have a statistically significant and positive effect on firm performance for both the performance measures. This provides support to the Schumpeterian view of innovation based on accumulated knowledge.

So, previous studies agree with each other that patents and citations counts are the most reliable way of measuring innovation. Unfortunately, patents and citations suffer from several imperfections (Chen et al., 2018) that has to be taken care of first. Firstly, it takes some time for a patent to be granted. This causes a truncation bias in the number of patents for the end of the sample period. Secondly, patents created at the end of the year of the sample could have fewer citations. Thirdly, the intensity of patenting and citations vary across industries. Hall, Jaffe and Trajtenberg (2001) and Seru (2014) name strategies to take care of these imperfections. So, this study follows these studies to adjust both patent and citation count. The first and partly the third imperfection is taken care of by dividing the number of patents for each firm by the average patent count of all firms in the industry classification and year. This variable is called Patent. To adjust for the second and third implication, the patent's non-self citation count will be scaled by the mean of the non-self citation count of all patents in the same industry classification and year. This variable is called Citation and is measured as the sum of the non-self citation counts across all patents applied for by a firm in a given year.

Next, it is also expected that the number of patents and citations will be highly skewed, because most of the firms will have only one granted green patent and no citations. Following the approach of Artz et al. (2010) the green innovation measures will transformed because of error term skewness problems if this will indeed be the case. So, to deal with the imperfections of patents and citations this study uses two measures of green innovation, namely the natural logarithm of the number of patents, in this study called; Log(PAT), and the natural logarithm of the number of non-self citations, in this study called; Log(CIT). All the firms in the sample have at least one granted green patent. However, this is not the case for citations as firms could have no citations on their granted green patents in a given year. This is a problem when using a natural logarithm and therefore the natural logarithm the number of citations plus 0.01 is used to deal with this problem (Artz et al., 2010). The difference between what is a green patent and what is not will be explained in chapter 4.

3.3.3 Control variables

Investing in green innovation most likely influences firm performance, but there are other factors that could also have a significant influence on the performance of a firm. The so called control variables related to firm characteristics could isolate the effects of the predictable influence of green innovation on firm performance (Gui-long et al., 2017).

The firm characteristics that are used the most in previous studies are: firm size[10], firm age[11], firm leverage[12] and an industry dummy[13]. Other less frequently used firm characteristics are for example: industry concentration (Ho et al., 2005; Ehie & Olibe, 2010; Loughran & Shive, 2011) and earnings per share (EPS) (Anagnostopoulou & Levis, 2008). In the context of this study, the most used control variables will be briefly described.

Firstly, firm size affects firm performance directly, because of the funds available, the diversification in operations, and controlling for more skilled managers specific to larger firms (Pramod, 2012; Ilyukhin, 2015). Abuhommous (2017) adds that a larger firm has the advantage of producing in larger quantities. So, large firms could be more efficient and this gives the firm the opportunity to take advantage of economies of scale (Gui-long et al., 2017; Huang & Hou, 2019). Zhou and Sadeghi (2019) agree and state that larger firms generally have less information asymmetry. Regarding patents, previous studies state that there may be economies of scales in generating them. This is due to the fixed costs of maintaining a legal department that manages patent-related issues and this suggests a positive influence of firm size on firm performance (Chen et al., 2018). Next to that, firm size also measures a firm's market power or the level of concentration in the industries in which the firm operates. This makes implementation of operations more effective, allows large firms to generate greater returns on assets and sales, and allows to capture more value as a proportion of the value of the production and this leads to a higher firm performance. However, on the other hand, strategic and operational activities of larger firms could also be less efficient than those of smaller firms when larger firms lose the control of top managers regarding these activities (Pramod et al., 2012). Huang and Hou (2019) agree and add that inefficient management activities could increase manufacturing costs when entering new markets and this negatively affects firm performance.

[10] Supporting literature: Mansfield, 1986; DeCarolis & Deeds, 1999; Ho et al., 2005; Chen et al., 2006; Oke et al., 2007; Rehfeld et al., 2007; Anagnostopoulou & Levis, 2008; Arora et al., 2008; Kale et al., 2009; Artz et al., 2010; Belderos et al., 2010; Ehie & Olibe, 2010; Li et al., 2010; Kumbhakar et al., 2011; Kober et al., 2012; Pramod et al., 2012; Aguilera-Caracuel & Ortiz-de-Mandojana, 2013; Leonidou et al., 2013; Choi & Williams, 2013; Seru, 2014; Ilyukhin, 2015; Frijns et al., 2016; Kim et al., 2016; Vithessonthi & Racela, 2016; Abuhommous, 2017; Gui-long et al., 2017; Chen et al., 2018; Ibhagui & Olokoyo, 2018; Sridharan & Joshi, 2018; Huang & Hou, 2019; Zhou & Sadeghi, 2019

[11] Supporting literature: Chen et al., 2006; Oke et al., 2007; Anagnostopoulou & Levis, 2008; Pramod et al., 2012; Choi & Williams, 2013; Seru, 2014; Frijns et al., 2016; Gui-long et al., 2017; Ibhagui & Olokoyo, 2018; Huang & Hou, 2019; Zhou & Sadeghi, 2019

[12] Supporting literature: Ehie & Olibe, 2010; Pramod et al., 2012; Choi & Williams, 2013; Seru, 2014; Frijns et al., 2016; Vithessonthi & Racela, 2016; Abuhommous, 2017; Chen et al., 2018; Sridharan & Joshi, 2018

[13] Supporting literature: Artz et al., 2010; Choi & Williams, 2013; Feeny & Rogers, 2013

Oke et al. (2007) state that there is an important link between innovation and business and economic growth. SMEs operating in high technology industries are more capable of adjusting to rapidly changing innovations than large firms. However, although these SMEs may have high intensity of R&D, larger firms with more slack can dedicate more resources to R&D. Therefore, the control variable firm size was used in this study, because it could have a significant effect on firm performance.

Firm size is measured differently among the studies investigating firm performance. Although, when studies are based on operating, accounting- and market-based measures, many studies use total assets to define the size of a firm (Anagnostopoulou and Levis, 2008; Kober et al., 2012). Next to total assets, when studies investigate productivity gains, studies use the number of employees as well to define the size of the firm (Chen et al., 2006; Arora et al., 2008; Kumbhakar et al., 2011; Kober et al., 2012). Kober et al. (2012) also uses total revenue to determine the size of the firm. Aguilera-Caracuel & Ortiz-de-Mandojana (2013) measure firm size using the total net revenues reported on each firm's balance sheet. But, there are also other ways of determining firm size. A couple of other studies measure firm size by the natural logarithm of total assets (DeCarolis & Deeds, 1999; Choi & Williams, 2013; Feeny & Rogers, 2013; Vithessonthi & Racela, 2016; Abuhommous, 2017; Sridharan & Joshi, 2018; Zhou & Sadeghi, 2019), the natural logarithm of market capitalization (Chen et al., 2018), the natural logarithm of the number of employees of the firm (Arora et al., 2008), or the natural logarithm of a firm's total or net sales (Ehie & Olibe, 2010; Pramod et al., 2012; Gui-long et al., 2017; Huang & Hou, 2019). The difference between total sales and net sales is that total sales includes inventories. Ehie and Olibe state that this avoids any compounding effects of firm size on firm performance by controlling for (dis)economies of scale. Using log transformations makes it easier to interpret the results, because changes in the logarithm domain represent relative changes in the original metric. Also, log transformations make the distribution of the data closer to a normal distribution. Frijns et al. (2016) also use a log-transformed measure, but they use the log-transformed market value in millions of GBP measured at the end of the calendar year to determine firm size. Next, Mansfield (1986) and Kale et al. (2009) use the natural log of the firm's net sales for the year. Ho et al. (2005) measure firm size by the natural logarithm of market capitalization of a firm at fiscal year-end. They state that market capitalization has the advantage of being an unbiased market measure of the size of a firm. They argue that the use of net sales or total assets could be affected by the accounting policies of a firm.

Secondly, firm age is associated with the production experience of a firm and therefore it is expected to have a positive influence on firm performance (Gui-long et al., 2017). Pramod et al. (2012) state that older firms with an established history could be expected to fare better in the stock market, because they can enjoy superior performance compared to newcomers and they could also avoid the liabilities of newness. Huang and Hou (2019) state that the cumulative learning approach of firms with experience tends to facilitate their operational approach and this leads to an increase in their firm performance. However, on the other hand, older firms are prone to inertia, and have less efficient adaptability and this could lead to a lower firm performance (Pramod et al. 2012). This makes the relationship between firm age and firm performance ambiguous. Many studies use the number of years since firm was established to determine the age of a firm (Frijns et al., 2016; Huang & Hou, 2019). Loughran & Shive (2011), however, use the number of years the firm has been listed on CRSP. Other studies also use the natural logarithm of the number of years since the firm was founded (Choi & Williams, 2013; Gui-long et al., 2017). Pramod et al. (2012) uses two measures of firm age, namely as the number of years since inception to the date of observation and the number of years since the incorporation of the firm.

Thirdly, firms use debt to decrease taxes paid. Leverage allows greater potential returns for investors that otherwise would have been unavailable. On the other hand, debt could also lead to potential losses if the investment becomes worthless, because then the firm still needs to pay the loan principal and all accrued interest on the loan. This increase in risk could decreases the performance of a firm (Pramod et al., 2012). Because, a high debt to equity ratio affects investments decisions on innovation resources and firm performance by increasing the likelihood of going bankrupt (Choi & Williams, 2013). However, Feng and Rong (2007) state that leverage should promote the market value of a firm when taxes shields are valuable or debt reduce agency problem. The results of other studies regarding leverage show that the performance of a firm is negatively affected by firms' leverage (Feng & Rong, 2007; Chadha & Oriani, 2009). Most studies calculate firm leverage as a firms' long-term debt divided by total assets (Ehie & Olibe, 2010; Pramod et al., 2012; Choi & Williams, 2013; Frijns et al., 2016; Vithessonthi & Racela, 2016; Abuhommous, 2017; Chen et al., 2018). However, Sridharan and Joshi (2018) measure firm leverage as total term liabilities divided by tangible net worth.

Fourthly, although less used, industry control and country control will also be used in this study. Studies that use the OLS regression analysis as their method also include an industry dummy and/or country dummy to control resp. for the distinction between industries and/or countries (Ho et al., 2005; Ehie & Olibe, 2010; Loughran & Shive, 2011; Aggelopoulos et al., 2016).

The control variables used in this study are firm size, firm age, firm leverage, and an industry and a country control dummy. Gui-long et al. (2017) state that using too many control variables could trouble statistical examination and therefore only these will be included in this study. Most studies that investigate any impact on firm performance consider at least the size, the age, and the leverage of a firm. Firstly, firm size will be measured as the natural logarithm of the net sales of the firm (Log(SIZE)). Firm size could have a positive or negative influence on firm performance. Larger firms have more resources and thus have operating advantages and are more efficient in using them. But, on the other side, strategic and operational activities of larger firms could also be less efficient than those of smaller firms when larger firms lose the control of top managers regarding these activities. Secondly, firm age will be measured as the natural logarithm of the number of years since the firm was incorporated (Log(AGE)). Since firm age is associated with production experience and an established history, it is expected that firm age could have a positive influence on firm performance. Thirdly, firm leverage will be used as a measure of firm risk and will be measured as long-term debt divided by total assets (LEV). An increase in risk of possible worthless investments could lead to a decrease in the performance of a firm and therefore it is expected to have a negative influence on firm performance. Fourthly, as already stated and regarding the institutional theory, the analysis will be controlled for industry and country fixed effects. These dummies will be based on the comparison of industries and countries with the most patents and the other industries and countries in the sample. A broader description of the industries and countries will be explained in chapter 4. Table III shows the definitions of the variables that will be used in this study and its supporting literature.

Variable name	Literature	Measurement of the variable
Dependent variables		
ROA	Vithessonthi & Racela, 2016; Abuhommous, 2017	EBIT / Total assets
ROE	Kale et al., 2009; Santos et al., 2014; Ilyukhin, 2015;	Net income / Equity
ROS	Vithessonthi & Racela, 2016	EBIT / Net sales
Profit Margin	Chan et al., 2016	EBIT / Operating income
Independent variables		
Log(PAT)	Griliches, Pakes, & Hall, 1986; Hsu, 2009; Artz et al., 2010; Czarnitzki & Kraft, 2012; Aguilera-Caracuel & Ortiz-de-Mandojana, 2013; Choi & Williams, 2013; Feeny & Rogers, 2013; Seru, 2014; Chen et al., 2018	Natural logarithm of the number of patents
Log(CIT)	Griliches, Pakes, & Hall, 1986; Czarnitzki & Kraft, 2012; Seru, 2014; Chen et al., 2018	Natural logarithm of the number of non-self citations
Control variables		
Log(SIZE)	Chen et al., 2006; Arora et al., 2008; Kumbhakar et al., 2011; Kober et al., 2012	Natural logarithm of net sales
Log(AGE)	Choi & Williams, 2013; Gui-long et al., 2017	Natural logarithm of the number of years since the firm was incorporated.
Firm leverage	Ehie & Olibe, 2010; Pramod et al., 2012; Choi & Williams, 2013; Seru, 2014; Frijns et al., 2016; Vithessonthi & Racela, 2016; Abuhommous, 2017; Chen et al., 2018	Long-term debt / Total assets
Industry control	Ho et al., 2005; Artz et al., 2010; Ehie & Olibe, 2010; Loughran & Shive, 2011; Choi & Williams, 2013; Feeny & Rogers, 2013; Aggelopoulos et al., 2016	A dummy variable that takes a value of one when the firm is operating in one of the patent-sensitive industries[14], and zero otherwise.
Country control	Choi & Williams, 2013; Feeny & Rogers, 2013	A dummy variable that takes a value of one when the firm is located in France, Germany, Japan or United States of America, and zero otherwise.

Table III: Definitions of Variables. ROA, return on assets. ROE, return on equity. ROS, return on sales. EBIT, earnings before interest and taxes. Log, the natural logarithm. PAT, the number of patents. CIT, the number of citations.

[14] Patent-sensitive industries consists of firms operating in division; manufacture of chemicals and chemical products (20), manufacture of basic pharmaceutical products and pharmaceutical preparations (21), manufacture of fabricated metal products, except machinery and equipment (25), manufacture of machinery and equipment n.e.c. (28), or class; extraction of crude petroleum (0610), support activities for petroleum and natural gas extraction (0910), manufacture of refined petroleum products (1920), manufacture of air and spacecraft and related machinery (3030), and research and experimental development on biotechnology (7211).

4 DATA & SAMPLE

4.1 Data Collection

The two main parts of data firms must have to be included in the sample are patent data and accounting and financial data, such as data on the balance sheet and profit and loss accounts of the firms. The gathering of the data will now be substantiated.

As already stated, many studies within the field of green innovation use a survey to gather their data. For example, Chen et al. (2006) used a survey to investigate their research wherein the managers of manufacturing, marketing, R&D, or environmental protection departments were the respondents. Gürlek and Tuna (2018) also used a survey to answer the question regarding green innovation. Their respondents were employees and junior, middle and senior-level managers. Lin et al. (2013) likewise used a survey to investigate the relationship between green product innovation performance and firm performance. This data was collected using a field study and the respondents were executives in charge of the manufacturing function from the selected firms. Ar (2012) also used a questionnaire for their study.

However, for this study patent data will be used to test the hypothesis. The study of Hsu (2009) uses R&D data and patent data as proxies for technological innovations. He states that patents are realized innovations, are more precise because of the territorial principle in patent laws, and are the intangible assets that are most actively traded in intellectual property markets. This makes patent data more reliable and informative than R&D data. Belderbos, Faems, Leten and Van Looy (2010) use this type of data as well, because they study the impact of technological activities on firm performance. Although this study is not completely in line with this green innovative study, it does have some overlap. It has the same types of hypotheses and they also investigate their independent variable by using patent data to construct indicators of this independent variable. They state numerous advantages of using patent indicators, namely documents of patents contain highly detailed information, patent data are objective, and patent data are publicly available. However, a small downside is that not all activities are patented, but no other indicator has the same level of detail as do patents. The studies of Belderbos et al. (2010), and Aguilera-Caracuel and Ortiz-de-Mandojana (2013) both use the European Patent Office (EPO) to gather their patent data. EPO is one of the two parts of the European Patent Organisation, wherein EPO executes and the Administrative Council supervises. EPO studies the European patent applications and decide whether or not a patent will be granted. The granted patents are called European patents. However, this does not mean that the owner of this patent must be European[15].

So, for testing the hypothesis, this study uses patent data as a proxy for green innovation. Patent data are better indicators than patent application data, but the latter has a broader indicator of the variety of the innovations of the firm. This means that patent application data will result in a more complete picture. Griliches, Pakes and Hall (1986) state that the year of application of the patent is preferred over the grant year, because the application year better represents the actual timing of the innovation. However, EPO its patent-granting decisions take some years. EPO states that its patent-granting process takes on average 20 months[16]. In 2014 they launched an initiative to accelerate the delivery of search results and thus to improve timeliness in substantive examination and opposition in order to streamline these stages of the patenting process with the goal of reaching an average of 12 months in 2020[17]. This means that firms who apply for a patent will not start to use the patented technology right away. Therefore, the publication date will be taken into account.

Following the study of Belderbos et al. (2010) and Aguilera-Caracuel and Ortiz-de-Mandojana (2013), this study will also use the database of EPO. As already stated, the number of patents and citations will be used as measures of green innovation. Regarding the green part, The Cooperative Patent Classification (CPC) uses the Y02 code as the classification of green patents[18]. CPC is an extension of the International Patent Classification (IPC) that is managed by EPO and the US Patent and Trademark Office[19]. Generally speaking, the Y02 code stands for "technologies or applications for mitigation or adaption against climate change". This code is divided into subcategories, wherein Y02A stands for "Technologies for adaptation to climate change", Y02B stands for "Climate change mitigation technologies related to buildings", Y02C stands for "Capture, storage, sequestration or disposal of greenhouse gases", Y02D stands for "Climate change mitigation technologies in information and communication technologies

[15] European Patent Office. "About us" epo.org
https://www.epo.org/about-us.html (accessed January 4, 2020)
[16] European Patent Office. "EPO Quality Report 2017" documents.epo.org
http://www. documents.epo.org (accessed November 28, 2019)
[17] European Patent Office. "Improving Timeliness" epo.org
https://www.epo.org/about-us/annual-reports-statistics/annual-report/2016/highlights/improving-timeliness (accessed November 28, 2019)
[18] Cooperative Patent Classification. "Technologies or applications for mitigation or adaptation against climate change" cooperativepatentclassification.org
http://www.cooperativepatentclassification.org/cpc/scheme/Y/scheme-Y02A.pdf (accessed November 29, 2018)
[19] European Patent Office. "Cooperative Patent Classification (CPC)" epo.org
https://www.epo.org/searching-for-patents/helpful-resources/first-time-here/classification/cpc.html (accessed November 29, 2018)

(ICT)", Y02E stands for "Reduction of greenhouse gas emissions, related to energy generation, transmission or distribution", Y02P stands for "Climate change mitigation technologies in the production or processing of goods", Y02T stands for "Climate change mitigation technologies related to transportation", and Y02W stands for "Climate change mitigation technologies related to wastewater treatment or waste management"[20]. In Appendix B an overview of examples for each of these codes will be provided. So, the number of granted patents with the Y02 code and its citations will be used to define the total number of green innovations of a firm for each year (Aguilera-Caracuel & Ortiz-de-Mandojana, 2013).

Next to having at least one patent with the Y02 code granted and published by EPO, firms must also have accounting and financial data available to be included in the sample. The patent database EPO has a collaboration with the financial database ORBIS, which makes it the perfect database to use for this study. ORBIS is a database that consists of detailed financial information of 300 million private firms worldwide. The database contains information on over 83 million patents worldwide. So, within ORBIS the patents of the EPO database will be collected. The data will consist of a sample of firms of green innovative firms who are the owners of a European patent granted and published by EPO. As aforementioned, this does not mean that all firms within the sample are European firms.

So, generally speaking, firms must have green patent data and accounting and financial data available to be included in the sample. Firstly, to go into more detail, the patents that will be selected are based on the criteria that these patents must be granted, published by EPO, indicated by CPC's Y02 code. Next to that, to be included in the sample the firms must also include data such as: the number of citations, the name of the current owner, the country code of the current owner, the NACE Rev. 2 Core industry code, the date of incorporation, and most importantly; the current owner's BvD ID number (Bureau van Dijk ID number). Because, the latter is a personalized identification number used by ORBIS to link, for example, the accounting and financial data of ORBIS itself with the patent data of EPO. ORBIS then automatically uses these BvD ID numbers to search for all the firms that hold these patents. Unfortunately, the matching process is currently not exhaustive, because not all applicants for patents are reported through the database of EPO and patents could also be applied for by individuals. Therefore, not all patents that will meet the criteria of the patents could be linked to a BvD ID number.

[20] European Patent Office. "CPC Scheme and Definitions" cooperativepatentclassification.org https://www.cooperativepatentclassification.org/cpcSchemeAndDefinitions/table (accessed December 12, 2019)

Secondly, it is needed to have an extended period of time (on average two to three years), beyond the announcement period, to investigate the full impact of the green innovation on the value of the firm (Artz et al., 2010; Chen et al., 2017). Because, most innovative activities are subject to information asymmetry between managers and external investors. For example, investors could be slow to recognize opportunities of increases in R&D expenditures. Therefore the data on these green patents of a firm will be gathered at time *t* - 3 to check the firm performance at time *t*. So, secondly, the patent data will run from 2007 to 2014 in order to calculate a 3-year lag for firm performance using accounting and financial data for the period of 2010 to 2017. These years are chosen based on the fact that ORBIS only has financial data on the latest 10 years (2010-2019) and the time-lag of 3 years for patents. The year 2018 and 2019 will be excluded from the sample, because of the bias towards the fact that newer patents have fewer citations and incomplete financial data.

Thirdly, for these firms to be included in the final sample they also must be listed and include accounting and financial data as: Operating P/L[21], total assets[22], P/L for Period[23], shareholders funds[24], net sales, operating revenue[25], and long term debt[26]. All firms must have a known value available for all accounting and financial data after three years of the granted green patent. These will be used to calculate the four measurements of firm performance and the control variables. For some robustness checks other samples will be used, but these firms have the same criteria.

4.2 Final Full Sample

Gathering all granted Y02 patents published between 2007 and 2014 gives a total of 54,652 green patents. With the BvD ID numbers ORBIS could link these patents to a total of 3,224 unique firms. After gathering the accounting and financial data of these firms, a total of 520 unique firms remain in the sample. These firms have data for at least one to a maximum of eight

[21] ORBIS definition: EBIT; all operating revenues - all operating expenses (gross profit-other operating expenses)
[22] ORBIS definition: fixed assets + current assets
[23] ORBIS definition: net income for the year. Before deduction of minority interests if any (profit after taxation + extraordinary and other profit).
[24] ORBIS definition: total equity (capital + other shareholders funds)
[25] ORBIS definition: total operating revenues; net sales + other operating revenues + stock variations. The figures do not include VAT. Local differences may occur regarding excises taxes and similar obligatory payments for specific market of tobacco and alcoholic beverage industries.
[26] ORBIS definition: long term financial debts (e.g. to credit institutions (loans and credits), bonds)

years. Of course, the same firm will not have the same data for different years. The criteria that reduced the number of unique firms the most was the criteria that the firms must be listed. This deletes all subsidiary firms, such as holdings. This is necessary, because in this way all firms within the sample could be checked for by using factual data represented in the annual reports to see if the data from ORBIS is reliable. 25 firms of the sample are randomly selected to check whether the accounting and financial figures correspondent with the annual reports. All prove to be accurate and reliable.

After analyzing these 520 firms, five industries were removed, because of the difficulty of comparing these industries with others[27]. These industries are represented below 1% in the sample as their contribution to the total sample was 0.60%. The same applies to countries. A total of eight countries with a contribution to the sample of 1.34% are removed[28].

Furthermore, all measures of variables are winsorized at 1% at each end of the distribution to minimize outlier effects and potential data errors (Kale et al., 2009; Ehie & Olibe, 2010; Frijns et al., 2016; Aggelopoulos et al., 2016; Vithessonthi & Racela, 2016). This gives a total of 450 unique firms with 1,314 firm year observations between 2007 and 2014, and with a total of 7,700 granted green patents and 9,087 citations. Table IV gives a more detailed overview of the total sample used in this study. In this table it can be seen that, for example, 180 of the 450 unique firms have at least one newly granted green patent in 2007. So, in 2007 all 180 firms together have a total of 1,290 newly granted green patents and these patents have received a total of 1,147 citations. Overall, the 450 unique firms appear a total of 1,314 times in the sample. Meaning that on average each firm is included in almost three of the eight years in the sample. In these eight years, these 450 unique firms have a total of 7,700 new green patents granted by EPO and these patents have received a total of 9,087 citations.

Year	Number of Firms	Number of Patents	Number of Citations
2007	180	1290	1147
2008	160	917	1096
2009	156	741	884
2010	147	771	1021
2011	182	975	862
2012	185	1094	1276
2013	153	891	1325
2014	151	1021	1476
	1314	7700	9087

Table IV: Overview sample. The table represents each year with the total number of firm year observations, patents, and citations included in the sample.

[27] Removed industries: Real estate activities, Education, Arts, entertainment and recreation, other service activities, and water supply; sewerage, waste management and remediation activities.
[28] Removed countries: Brazil, Canada, China, Greece, New Zealand, Poland, Singapore, and Slovenia.

4.3 Distributions

4.3.1 Industry Distribution

NACE Rev. 2 Main Section	**NACE division**	**Frequency**	**Percent**
C - Manufacturing	10-33	1121	85.3
Manufacture of food products	*10*	*4*	*0.3*
... of beverages	*11*	*5*	*0.4*
... of textiles	*13*	*4*	*0.3*
... of wearing apparel	*14*	*1*	*0.1*
... of paper and paper products	*17*	*6*	*0.5*
Printing and reproduction of recorded media	*18*	*3*	*0.2*
... of coke and refined petroleum products	*19*	*20*	*1.5*
... of chemicals and chemical products	*20*	*140*	*10.7*
... of basic pharmaceutical products and pharmaceutical preparations	*21*	*24*	*1.8*
... of rubber and plastic products	*22*	*41*	*3.1*
... of other non-metallic mineral products	*23*	*22*	*1.7*
... of basic metals	*24*	*35*	*2.7*
... of fabricated metal products, except machinery and equipment	*25*	*25*	*1.9*
... of computer, electronic and optical products	*26*	*212*	*16.1*
... of electrical equipment	*27*	*96*	*7.3*
... of machinery and equipment n.e.c.	*28*	*189*	*14.4*
... of motor vehicles, trailers and semi-trailers	*29*	*182*	*13.9*
... of other transport equipment	*30*	*96*	*7.3*
... of furniture	*31*	*2*	*0.2*
Other manufacturing	*32*	*14*	*1.1*
D - Electricity, gas, steam and air conditioning supply	35	61	4.6
B - Mining and quarrying	05-09	37	2.8
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	45-47	29	2.2
M - Professional, scientific and technical activities	69-75	23	1.8
J - Information and communication	58-63	20	1.5
F - Construction	41-43	12	0.9
H - Transportation and storage	49-53	11	0.8
Total		1314	100

Table V: Industry Distribution. The table represents each industry with its NACE code and the total number of firm year observations of that industry. The divisions of Section C – Manufacturing are also shown.

The industries included in the sample are based on the NACE Rev. 2 classification codes. NACE consists of a hierarchical structure, where the first level consists of sections identified by an alphabetical code, the second level consists of divisions identified by a two-digit numerical code, the third level consists of groups identified by a three-digit numerical code, and the fourth level consists of classes identified by a four-digit numerical code. The groups and classes describe a specific activity[29]. A total of 40 industries classified by this code are included in the sample. These 40 industries could be designated to eight main sections shown

[29] Eurostat. "NACE Rev. 2" ec.europa.eu https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF (accessed January 8, 2020)

in Table V. The table shows that most of firms that have a granted green patent operate in the manufacturing industry (85.3%), therefore the divisions of this section are also shown.

Mansfield (1986) found that patents do have a positive impact on firm performance, but they are important in only a relatively small number of industries. He finds that the protection of patents is mostly essential in the pharmaceuticals and chemicals industries, but it was also essential in the petroleum, machinery, and fabricated metal products industry. It was less important in the electrical equipment, office equipment, motor vehicles, instruments, primary metals, rubber, and textiles industries. Additional support was provided by MacDonald (2004) who also names the pharmaceutical industry as the most important industry. Arora, Ceccagnoli, and Cohen (2003) find a positive relation between patents and firm performance in the drugs and biotechnology industry also. Artz et al. (2010) use longitudinal data from a cross-industry study of 272 firms over a recent 19-year period (1986-2004). They control for industry effects since multiple industries are represented in the sample. They agree with Mansfield (1986) and find that patents play a more important protection role in some industries, such as chemical products, pharmaceutical, than in other industries, such as motor vehicles, rubber and textiles. The reason for these industries to be more important is due to the fact that firms within these industries generally do not prefer to rely on trade secret protection when patent protection is possible (Mansfield, 1986). Patents can often be invented relatively cheaply and the cost of upholding their validity or proving that the patent had been infringed upon is too high (Artz et al., 2010).

Based on previous literature, an industry dummy will be added that takes the value of 1 if the patent is from division; manufacture of chemicals and chemical products (20), manufacture of basic pharmaceutical products and pharmaceutical preparations (21), manufacture of fabricated metal products, except machinery and equipment (25), manufacture of machinery and equipment n.e.c. (28), or class; extraction of crude petroleum (0610), support activities for petroleum and natural gas extraction (0910), manufacture of refined petroleum products (1920), manufacture of air and spacecraft and related machinery (3030), and research and experimental development on biotechnology (7211)[30]. These divisions and classes consist of 36.53% of the total sample.

[30] Eurostat. "NACE Rev. 2" ec.europa.eu https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF (accessed January 8, 2020)

4.3.2 Country Distribution

Country	Number of firm years	Percent
Japan (JP)	503	38.3
United States of America (US)	260	19.8
Germany (DE)	151	11.5
France (FR)	133	10.1
Italy (IT)	37	2,8
Finland (FI)	29	2,2
Sweden (SE)	26	2,0
Norway (NO)	25	1,9
Great Britain (GB)	22	1,7
Taiwan (TW)	21	1,6
Denmark (DK)	19	1,4
The Russian Federation (RU)	16	1,2
Austria (AT)	15	1,1
Switzerland (CH)	14	1,1
Belgium (BE)	13	1,0
The Netherlands (NL)	11	0,8
Turkey (TR)	10	0,8
Spain (ES)	9	0,7
Total	1314	100

Table VI: Country Distribution. The table represents each country with the total number of firm year observations of that country.

Table VI shows the distribution of all countries included in the sample of 1,314 firm year observations. The firms of these countries are the owners of at least one green patents that is granted by EPO. As can be seen, Japan (38.3%), United States of America (19.8%), Germany (11.5%), and France (10.1%) are the four countries that represent almost four fifths (79.7%) of the sample. Meaning that these four countries are leaders when it comes to investing in green innovation. This is as expected, because the United States of America, Japan, Germany and France are resp. the first, third, fourth, and seventh country with the highest GDP in the world[31]. It however seems surprising that China and India are not represented in the sample as they have resp. the second and fifth highest GDP in the world. But, firms operating in China register by China National Intellectual Property Administration (CNIPA) and firms operating in Korea register by Korean Intellectual Property Office (KIPO).

Furthermore, it is interesting to see if there are any differences on the impact of green patents granted by EPO between the top four countries and non-top four countries. Therefore, a country dummy will be added which takes a value of one for the countries Japan, United States of America, Germany, and France, and zero otherwise.

[31] International Monetary Fund. “GDP, current prices in Billions of U.S. dollars” imf.org https://www.imf.org/external/datamapper/NGDPD@WEO/OEMDC/ADVEC/WEOWORLD (accessed January 8, 2020)

5 RESULTS

In this chapter the model used in this study will be performed and analyzed to find evidence for the hypothesis. First an explanation of the descriptive statistics and correlation matrix of all variables used in this study will be given. Based on the latter, multicollinearity will be checked. After this, the results of the main analyses will be reported and an extensive analysis will be given. The results of all models within the main analysis of this study will be linked to previous studies and theories.

5.1 Descriptive Statistics

DESCRIPTIVE STATISTICS FULL SAMPLE 2007 – 2014

Variables	N	Mean	Std. Dev.	Min	Max	Q1	Median	Q3
ROA (%)	1314	5.07	11.03	-68.37	22.21	3.19	6.24	9.55
ROE (%)	1314	7.76	28.17	-157.10	119.95	4.40	9.83	16.02
ROS (%)	1314	4.59	20.09	-113.99	28.54	3.92	7.31	11.14
Profit Margin (%)	1314	4.66	19.45	-112.03	27.98	3.88	7.30	11.00
Number of Patents	1314	5.86	13.24	1	166	1	2	4
Number of Citations	1314	6.92	20.95	0	193	0	0	4
Firm Size (× € 1,000,000)	1314	21,872.74	36,617.13	11.64	200,290.24	1,526.77	6,550.38	23,622.44
Firm Age (years)	1314	70.62	38.18	5	164	37	71	97
Firm Leverage (%)	1314	15.05	10.85	0	48.38	6.83	14.15	21.35
Industry Control	1314	0.37	0.48	0	1	0	0	1
Country Control	1314	0.80	0.40	0	1	1	1	1

Table VII: Descriptive Statistics full sample. ROA, return on assets. ROE, return on equity. ROS, return on sales.

Table VII presents the descriptive statistics for the final sample of firms used in this study. It reports the mean, standard deviation, the minimum and maximum, and the quartiles for the dependent, independent, and control variables.

In general, the descriptive statistics show that all four firm performance measures have a positive mean. This means that all firms who invested in green innovation between 2007 and 2014 had on average an increase in their firm performance between 4.66% (Profit Margin) and 7.76% (ROE) three years later, based on the four performance measures used in this study. This is somehow in line with the study of Choi and Williams (2013) who unfortunately only report a concise table of descriptive statistics. Their measure of ROA has a mean of 5.70%, which correspondents with the mean of 5.07% for ROA used in this study. However, their standard deviation is a bit larger (15.90%) as the one in this study (11.03%). Moreover, Santos et al. (2014) report a maximum of ROS of 63.80%, which is contrary to the maximum of ROS reported in this study (28.54%). However, their database spread out quite much, because they report a minimum of -4.196.10% and a maximum of 644.60% for their measure of ROE. But, this is not a problem for them as they use SEM as their method, which has no distributional assumptions. So that means that data may be non-normal, skewed, and kurtotic.

Moreover, the table reports that all firms have at least one granted green patent and the firm with the most has 166 of them. The firm who reports the most granted green patents between 2007 and 2014 is Siemens Aktiengesellschaft (AG) from Germany, the largest industrial manufacturing firm of Europe. They offer a variety of electrical engineering- and electronics-related products and services[32]. Examples of their granted green patents are a method and device for conversion of carbon monoxide, a device to accumulate electric energy comprising battery, a device for controlling energy transmission between transmission units in e.g. electric cars, a power plant running on organic fuel with a carbon dioxide separator, and a windmill generator. So, it is safe to say that Siemens AG contributes to an environmental friendly society. A few other new European green patents granted by EPO in 2014 with its number of citations are listed in Appendix C.

Next to that, the 1,314 firm year observations included in the sample have an average of 5.86 granted European green patents each year with a standard deviation of 13.24, which equates to the total of 7,700 granted European green patents. However, most of the firms do not have that many as the median is two and the third-quartile is only four. In the study of Aquilera-Caracuel and Ortiz-de-Mandojana (2013) the maximum of granted green patents a firm has in a given year is almost twice as this study, namely a total of 320. They also report a much higher median and standard deviation of granted green patents, namely 23.33 and 52.75 respectively. However, this is due the fact that this study only include firms that have registered a higher percentage of granted green patents for their period of time, because they are interested in firms that consistently have developed green innovative behaviour.

Additionally, these granted green patents could also cited by others. The number of citations range from zero to 193. The descriptive statistics show that each granted green patent has an average of 6.92 citations with a standard deviation of 20.95, which equates to the total of 9,087 citations. Although, most of them have none, as the median is zero and the third-quartile is only four citations. Meaning that at least half of the firms in the sample did not have a citation for any of the green patents granted that specific year. Therefore, a subsample analysis for only firms that report at least one citation will be performed as a robustness check to see if the results will differ or not. Next to that, given the non-normal distributions of the number of

[32] Siemens. "Consumer products" new.siemens.com
https://new.siemens.com/global/en/products/consumer.html (accessed January 9, 2020)

citations, another robustness check will be performed where a dummy variable for the number of citations will be used as an alternative measure of green innovation as well.

Furthermore, the firms included in the sample range in firm size from € 11.64 million in net sales to around € 200 milliard in net sales with an average of almost € 22 milliard. These firms range in age from 5 till 164 years with an average of 70.62 years. Also, firms included in the sample show no signs of financial distress as the firm leverage ranges from debt-free to 48.38%. Because, a higher long-term debt to equity ratio affects investments decisions on innovation resources and firm performance by increasing the likelihood of going bankrupt (Choi & Williams, 2013). Although, a ratio around 50% is not associated as a completely healthy ratio, it is also no sign of going bankrupt.

5.2 Correlation Matrix

5.2.1 Pearson's Correlation Matrix

CORRELATION MATRIX FULL SAMPLE 2007 – 2014

Variables	1	2	3	4	5	6	7	8	9
1. ROA	1	0.512**	0.858**	0.865**	-0.064*	0.062*	0.375**	0.280**	-0.022
2. ROE		1	0.441**	0.447**	-0.006	0.080**	0.263**	0.160**	-0.005
3. ROS			1	0.997**	-0.031	0.055*	0.448**	0.323**	0.037
4. Profit Margin				1	-0.031	0.055*	0.446**	0.321**	0.042
5. Log(PAT)					1	0.249**	0.261**	0.051	0.022
6. Log(CIT)						1	0.263**	0.078**	-0.017
7. Log(SIZE)							1	0.403**	0.227**
8. Log(AGE)								1	0.060*
9. Firm Leverage									1

Table VIII: Correlation Matrix full sample. ROA, return on assets. ROE, return on equity. ROS, return on sales. Log(PAT), the natural logarithm of the number of patents. Log(CIT), the natural logarithm of the number of citations. Log(SIZE), the natural logarithm of net sales. Log(AGE), the natural logarithm of the number of years since incorporation.
* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

To further explore the correlations among the variables in this study, Pearson's correlation matrix was computed. Table VIII presents the results of this correlation coefficient analysis for the dependent, independent, and control variables.

Firstly, the dependent and control variables are examined in order to check whether they are correlated to the independent variables. The table reports that the number of citations is positively and significantly correlated to all four performance measures, which is supportive to the hypothesis. However, the number of patents is negatively related with all four performance measures and the correlation between the number of patents and ROA is even significant, which is not supportive to the hypothesis. Although, this coefficient is weak (-0.064) and only significant at the 10% level. Next to that, not surprisingly, ROA, ROE, ROS and Profit Margin all have significant positive correlations with each other. They are all measures of firm performance and therefore correlate with each other. Profit Margin even shows a correlation coefficient of 0.997 with ROS[33]. Moreover, both the number of patents and citations show positive and significant correlation coefficients with firm size. With firm age as well, only the correlation between the number of patents and firm size is not significant. Meaning that, based on these correlation analysis, larger and older firms could have more resources and experience to devote to generating green innovative activity. The control variable firm leverage also shows a positive correlation with the number of patents, but a negative correlation with the number of citations, but these correlations are not significant.

Secondly, the control variables are examined. Both firm size and firm age correlate significantly and positively with all firm performance measures, with each other, and with firm leverage at the 5% level. Only the correlation between firm age and firm leverage is not significant at the 5% level, but at the 10% level. The correlation between these two control variables and the four dependent variables is as expected, because larger and older firms, and thus more mature and established, are on average better able to efficiently make profit that increases firm performance. Moreover, the positive significant correlation between firm size and firm age was to be expected as well as older firms have on average more time to acquire more total assets compared to younger firms. Although, instead of a positive correlation a negative correlation between firm size and firm leverage would have been more likely as larger firms with more total assets are on average more mature and more established and thus have to depend less on debt. Lastly, it was also more likely that firm leverage was negatively correlated with the dependent variables as the cost of debt lowers the ability of generating more profits and thus a better firm performance. Firm leverage only shows a negative correlation with ROA and ROE. However, the correlation for all four dependent variables are not significant.

5.2.2 Multicollinearity

One of the main problems that could arise in statistics is the problem of multicollinearity. Multicollinearity is present when two or more independent variables in a multiple regression model are highly linearly related. Meaning that there is a strong correlation between the independent variables. This statistical problem makes it hard to estimate the coefficients

[33] This is because of the fact that both have EBIT as the numerator and the difference in the denominator is that ROS is divided by net sales and Profit Margin by net sales + other operating revenues + stock variations. So, if a firms lacks the last two, the calculation of ROS and Profit Margin have the same result.

accurately. It could also affect the standard errors and because of that variables could be incorrectly displayed as (in)significant.

There are some ways to detect multicollinearity. Firstly, the simplest and most reliable one is by checking the correlation matrix (Pramod et al., 2012; Abuhommous, 2017; Gui-long et al., 2017; Zhou & Sadeghi, 2019). Multicollinearity will not be a great problem when the correlation coefficients between the independent variables are below 0.30 (Vithessonthi & Racela, 2016). But, when the correlation coefficient between two measures is above 0.30 and statistically significant, the variables will be added separately in the regressions. Secondly, multicollinearity could also be tested by examining the VIF values of the independent variables as well. This provides an index that measures how much the variance of an estimated regression coefficient is increased because of the multicollinearity. A value of 1 means that there is no correlation between the independent variables. A value above 3 means that there probably exists some multicollinearity, a value above 5 means that it is very likely there is a multicollinearity problem, and a value above 10 definitely indicates multicollinearity that causes inevitable problems (Ehie & Olibe, 2010).

Both these two approaches are used in this study. Looking at the correlation matrix one might expect multicollinearity as the correlation between the two independent variables is 0.249, which is not above the threshold of 0.30, but still close to it. However, the VIF approach gives a value of 1, meaning that there is no multicollinearity between the two independent variables used in this study. The value of 0.249 is lower than expected, because both are measures of the same. However, Hall et al. (2005) report a correlation of 0.220 as well and DeCarolis and Deeds (1999) report an even lower correlation (0.070) between the number of patents and citations.

Furthermore, the control variable firm size has high correlations with all other variables and even has a correlation of 0.261 with the number of patents and a correlation of 0.263 with the number of citations. Both are also not above the threshold of 0.30, but are also really close. This means that firm size most likely strongly affects the number of patents and citations. So, this could lead to incorrectly displaying these two as positively or negatively (in)significant when firm size is included in the regression as well. Therefore, firm size will be monitored closely to see whether this control variable indeed has too much influence. Artz et al. (2010) also report that their control variable firm size was significantly correlated with their independent variable. However, their approach was by removing the control variable from the analysis and this study will not follow that approach.

5.3 OLS Regression Results

5.3.1 Full Sample Results

To test the hypothesis of this study an OLS regression analysis will be performed. This section reports the results of the independent variables number of patents/citations with its control variables on the four measures of firm performance as the dependent variables for the full sample. Only the results of ROE as the firm performance measure will be reported in this section Appendix D reports the results of the other three firm performance measures. Any differences between these three measures and ROE will be explicitly described.

Furthermore, the tables report a couple of models wherein the first model (1) will be used as a benchmark model in order to see the impact of the independent variable in the other models. The last model (5) will be the full model and shows how all variables are related to the dependent variable and the other models (2), (3), and (4), the so called specific models, show how specific combinations of variables are related to the dependent variable. Panel A (B) reports the results of the regression for the number of patents (citations) as the independent variable.

OLS REGRESSION ROE FULL SAMPLE 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-49.84	***	-16.49	***	4.16	**	-16.06	***	-53.38	***
	(-8.74)		(-3.79)		(1.99)		(-3.63)		(-8.97)	
Log(PAT)			0.51		1.18		0.52		-3.37	**
			(0.31)		(0.71)		(0.32)		(-2.05)	
Log(SIZE)	7.85	***							8.34	***
	(8.82)								(9.06)	
Log(AGE)	3.70		12.25	***			12.31	***	3.53	
	(1.48)		(5.16)				(5.18)		(1.41)	
LEV	-0.17	**			-0.02		-0.04		-0.18	**
	(-2.45)				(-0.31)		(-0.57)		(-2.53)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	26.546	***	12.935	***	6.182	***	10.408	***	22.877	***
Adj. R2	8.9%		3.5%		1.6%		3.5%		9.1%	
Obs.	1314		1314		1314		1314		1314	

OLS REGRESSION ROE FULL SAMPLE 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-49.84	***	-12.48	***	7.61	***	-12.14	***	-48.11	***
	(-8.74)		(-2.75)		(3.23)		(-2.64)		(-7.75)	
Log(CIT)			0.76	***	0.86	***	0.75	***	0.19	
			(2.84)		(3.20)		(2.82)		(0.70)	
Log(SIZE)	7.85	***							7.69	***
	(8.82)								(8.36)	
Log(AGE)	3.70		11.78	***			11.84	***	3.75	
	(1.48)		(4.97)				(4.99)		(1.50)	
LEV	-0.17	**			-0.02		-0.03		-0.17	**
	(-2.45)				(-0.21)		(-0.49)		(-2.38)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	26.546	***	14.999	***	8.660	***	12.039	***	22.194	***
Adj. R2	8.9%		4.1%		2.3%		4.0%		8.8%	
Obs.	1314		1314		1314		1314		1314	

Table IX: OLS regression results on ROE for full sample[34]. Log(PAT) is natural logarithm of the total number of granted green patents of the firm. Log(CIT) is the natural logarithm of the total number of citations of all granted green patents of the firm. Log(SIZE) is the natural logarithm of the net sales of the firm. Log(AGE) is the natural logarithm of the number of years since the date of incorporation of the firm. LEV is the ratio of long-term debt to total assets of the firm. Results are controlled for industry and country fixed effects. Panel A (B) reports the results of the regression for the number of patents (citations) as the independent variable. 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 IX presents the OLS regression results of the number of patents/citations as the independent variable with its control variables on ROE as the firm performance measure for

[34] Independent variables are taking values from 2007-2014, and control and dependent variables are taking values from 2010-2017, because of the 3-year lag.

the full sample. Firstly the benchmark models (1) will be described and thereafter the specific models (2), (3), and (4), and finally the full model (5).

The benchmark models (1) show that control variables firm size and firm age are positively related with all four performance measures. These relationships are also significant at the 1% level in almost all benchmark models, meaning that larger and older firms have on average a higher firm performance. The control variable firm leverage is negatively and significantly related to the performance measures, meaning that firms with a higher debt issue have a lower firm performance.

Furthermore, the results of the specific models (2), (3), and (4) show that there is no relationship between the number of patents and ROE as the coefficients are not statistically significant. However, the number of citations is positively related to ROE and this relationship is statistically significant at the 1% level. This concludes that investing in green innovation, measured by the number of citations, does have a positive influence on the performance of the firm, which confirms the hypothesis. These results are somehow in line with the innovation studies of Li et al. (2010), Choi and Williams (2013), Feeny and Rogers (2013), and Huang and Hou (2019), because they all find that the number of patents as the innovation indicator is also positively related to the performance of the firm as their coefficients are statistically significant. Although the results do not show a statically relationship between the number of patents and ROE, this relationship still shows the positive sign. Regarding green innovation studies, this result confirms the study of Chiou et al. (2011), Ar (2012), Lin et al. (2013), and Chan et al. (2016), who all find that green innovation is significantly and positively related to firm performance. This proves that the positive effects of green innovation, namely reducing pollution and limiting hazardous and toxic waste and thus reducing the cost of disposal and improving the green efficiency and response to external environmental pressure from customers, all ultimately contribute to a better firm performance (Chiou et al., 2011).

Appendix D reports the results of the other three performance measures. Interestingly, looking at ROA as the performance measure, the number of citations still shows a positive and significant relationship with ROA in model (2), (3), and (4), but the number of patents shows a negative and significant relationship with ROA in model (2) and (4). Artz et al. (2010) find the same result for the relationship between patents and ROA. This could be due to the fact that the sample consists of all firms that have at least one granted green patent. So, it is possible that having only one granted green patent as a firm does not have that big of an impact on the performance of a firm. Because, in model (2), (3), and (4) three out of four performance measures show no significant relationship between the number of patents and the performance measure, and is only negative and significant related to ROA. The performance measure ROA may turn out negative, while that is not due to only that one granted green patent. However, the negative sign still calls into question the value of patents as protect mechanisms. Artz et al. (2010) argue that it is possible that patents may only boost firm performance indirectly through their positive effect on product innovations. They also argue that not all patented technologies are actually converted into products. In this way, a patent could decrease the competitive position of a firm, because managers think they are invincible against competitors and thus do not develop other complementarities and skills that are needed to compete, like management, production, and marketing. Also, the granting procedure of patents is expensive and this combined with low returns directly from those patents could explain the negative relationship. Therefore, regarding to green innovation, the number of citations is probably a better measure of green innovation than the number of granted green patents. Because, the more citations a granted green patent has, the more firms have used that particular granted green patent to file for a green patent themselves. And of course, other firms only continue to embroider on successful granted patents. So, one could argue that the more citations a granted green patent has, the more it turned out to be successful. Making citation count a measure of success.

Moreover, firm age shows a positive relation with all four performance measures for all models and this relationship is also significant at the 1% level in most of the models, which is in line with previous literature (Pramod et al., 2012; Gui-long et al., 2017; Huang & Hou. 2019). Firm age is often associated with production experience, which could have a positive influence on the performance of a firm. Pramod et al. (2012) state that older firms are expected to fare better on their market. They can avoid the liabilities newcomers have. Furthermore, firm leverage shows a negative relationship with the four performance measures in all full models (5) and is significant at the 5% level. Which is in line with previous literature as well as they find a negative and significant relationship with the performance measure (Feng & Rong, 2007; Chadha & Oriani, 2009). Pramod et al. (2012) state that debt could lead to potential losses if the green innovation investment becomes worthless, because then the firm still needs to pay the loan principal and all accrued interest on the loan. This increase in risk decreases the performance of a firm. So, a high leverage level affects investments decisions on innovation resources and firm performance by increasing the likelihood of going bankrupt (Choi & Williams, 2013).

Furthermore, the results of using ROS and Profit Margin as the dependent variable show extremely weak results and almost no significance at all for both the independent variables in models (2), (3), and (4). Only the relationship between the number of citations and the two performance measures is positive and significant at the 5% level in model (3) when only leverage is included as a control variable. However, only resp. 0.8% and 0.9% of the variance of the dependent variable is explained by the independent variables in this model.

Lastly, in the full model (5) the control variable firm size is also included in the regression and expectedly the regression reports completely different results. Using ROE as the dependent variable, the number of citations as the independent variable still shows a positive sign, but loses all its significance. The number of patents is even negatively and significantly related to ROE at the 5% level. Almost the same applies to the regression wherein ROA is used as the dependent variable, but here the number of citations also shows a negative but weak sign. For ROS and Profit Margin this relationship suddenly becomes significant at the 5% level. Meaning that for larger firms the more patents/citations, the lower its performance. Mansfield (1986) states that many economists seem to believe that for smaller firms patent protection tends to be more important than for larger firms. Although, Mansfield does not find evidence regarding this statement, but this could be due to the fact that his study is not concerned with very small firms (sales below $ 25 million). Therefore, it is interestingly to split the sample by the median of firm size as a robustness check (Loughran & Shive, 2011; Vithessonthi & Racela, 2016).

In conclusion, the results partly support the hypothesis that green innovation affects firm performance positively as the number of citations indeed show the positive and significant sign with ROE and ROA and partly for ROS and Profit Margin when firm size is not included, but the number of patents does not. Regarding citations, this is in line with the resource-based theory as the theory states that unique resources and capabilities of a firm are the key drivers of competitive advantage and a better performance of a firm. Green innovation is one example of such a unique resource, because a firm could use it to differentiate itself from others. Therefore, the positive and significant relationship between green innovation and firm performance was as expected. This result is also consistent with the innovation theory of Schumpeter (1934) as he stated almost a century ago that adaptable firms that try new creative ways of operating are more likely to outperform firms that do not, especially in a competitive environment. This is still the case nowadays as the more successful granted green patents show a higher firm performance. Because, the number of citations clarifies the number of other firms that are trying to copy or improve that granted green patent and could thus arguably be a measure of its success. These firms could on average have a stronger market position, because the new ways of using the knowledge, technology and resources of the firm could bring new opportunities.

6 ROBUSTNESS CHECKS

Robustness checks are performed to examine if the results of the main analysis are consistent, robust and provide reliable outcomes. If the coefficients are plausible and robust, this is commonly interpreted as evidence of structural validity (Lu & White, 2014). The robustness checks that are performed to test the hypothesis of this study as well are a fixed/random effects model for the full sample, and extra OLS regression checks for: the full sample split by the median of size, a 2-year lag sample, a sample consisting of firms operating only in patent-sensitive industries, a sample consisting of firms with at least one citation, a 2010-2014 sample with using a 2-year and 3-year lag for firm performance improvement as the replacement of the dependent variable, and a sample using a citation dummy as the replacement of the number of citations. The sections firstly describes the descriptive statistics and correlation matrices that are reported in appendix E till K. Any differences with the full model of the main analysis will be described. Thereafter, the results of the robustness test will be reported. Again, only the results of ROE as the firm performance measure will be reported in this section. Appendix E till K report the results of the other three firm performance measures as well. Any differences between the results of the main analysis and robustness tests will be substantiated.

Same as before, the tables report a couple of models wherein the first model (1) will be used as a benchmark model in order to see the impact of the independent variable in the other models. The last model (5) will be the full model and shows how all variables are related to the dependent variable and the other models (2), (3), and (4) show how specific combinations of variables are related to the dependent variable. Panel A (B) reports the results of the regression for the number of patents (citations) as the independent variable.

6.1 Fixed/Random Effects model

The first robustness check is the fixed/random effects model. Previous studies with similar hypothesis use a combination of the OLS regression with this model as well (Kumbhakar et al., 2011; Loughran and Shive 2011; Ortega-Argilés et al., 2011; Vivarelli and Voigt, 2011; Pramod et al., 2012; Ilyukhin, 2015; Huang and Hou, 2019). The reason for this is the disadvantage of using an OLS regression for this sample as it ignores the panel structure of the data. An OLS regression thus assumes that observations are serially uncorrelated and that the errors across individual and time are homoskedastic, meaning that the estimates of the regression are inefficient when these errors are not homoskedastic. However, the measures of green innovation change a lot over time for particular firms. No firm has the same number of patents and citations over all eight years. Table X, which is an extension of Table IV, shows that the number of patents a firm has each year ranges from 4.75 in 2009 to 7.17 in 2007. Also the number of citations a patent receives ranges from 0.88 for patents in 2011 and 1.49 in 2013. These facts make it interesting to perform a fixed/random effects model as well.

Year	Number of Firms (NoF)	Number of Patents (NoP)	Number of Citations (NoC)	NoP per firm	NoC per patent
2007	180	1290	1147	7.17	0.89
2008	160	917	1096	5.73	1.20
2009	156	741	884	4.75	1.19
2010	147	771	1021	5.24	1.32
2011	182	975	862	5.36	0.88
2012	185	1094	1276	5.91	1.17
2013	153	891	1325	5.82	1.49
2014	151	1021	1476	6.76	1.45

Table X: Detailed overview sample. The table is an extension of Table IV and represents the average number of patents per firm and number of citations per patent for each year as well.

By performing the Hausman test one finds out whether to use the fixed or random effects model. The null hypothesis is that random effects model is the preferred model and the alternative hypothesis speaks in favour of the fixed effects model. In this study, the null hypothesis is rejected, meaning that a fixed effects model is preferred. This is in line with the study of Ilyukhin (2015). He studies the same type of relationship, has an unbalanced panel dataset too and also use a fixed effects model as the null hypothesis of the Hausman test is rejected as well.

FIXED EFFECTS MODEL ROE FULL SAMPLE 2007 – 2014
Panel A

Model	1	2	3	4	5
Constant	-0.48	-0.49	-0.76	0.33	-0.48
	(-0.77)	(-0.79)	(-1.32)	(0.77)	(-0.77)
Log(PAT)		-0.01	-0.01	-0.01	-0.01
		(-0.45)	(-0.39)	(-0.41)	(-0.46)
Log(SIZE)	0.17 *	0.17 *	0.13		0.17 *
	(1.80)	(1.85)	(1.48)		(1.81)
Log(AGE)	-0.31	-0.33		-0.14	-0.32
	(-1.17)	(-1.23)		(-0.56)	(-1.19)
LEV	-0.07		-0.08	-0.09	-0.07
	(-0.40)		(-0.52)	(-0.55)	(-0.40)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
F-statistic	1.290	1.310	0.890	0.270	1.020
Obs.	1314	1314	1314	1314	1314

FIXED EFFECTS MODEL ROE FULL SAMPLE 2007 – 2014
Panel B

Model	1	2	3	4	5
Constant	-0.48	-0.52	-0.78	0.30	-0.51
	(-0.77)	(-0.83)	(-1.35)	(0.69)	(-0.81)
Log(CIT)		-0.00	-0.00	-0.00	-0.00
		(-0.33)	(-0.48)	(-0.33)	(-0.35)
Log(SIZE)	0.17 *	0.17 *	0.13		0.17 *
	(1.80)	(1.84)	(1.50)		(1.80)
Log(AGE)	-0.31	-0.31		-0.12	-0.30
	(-1.17)	(-1.16)		(-0.50)	(-1.12)
LEV	-0.07		-0.09	-0.09	-0.07
	(-0.40)		(-0.52)	(-0.56)	(-0.41)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
F-statistic	1.290	1.280	0.910	0.250	1.000
Obs.	1314	1314	1314	1314	1314

Table XI: Fixed effects model results on ROE for full sample[35]. Log(PAT) is natural logarithm of the total number of granted green patents of the firm. Log(CIT) is the natural logarithm of the total number of citations of all granted green patents of the firm. Log(SIZE) is the natural logarithm of the net sales of the firm. Log(AGE) is the natural logarithm of the number of years since the date of incorporation of the firm. LEV is the ratio of long-term debt to total assets of the firm. Results are controlled for year and firm fixed effects. Panel A (B) reports the results of the regression for the number of patents (citations) as the independent variable. T-values are reported in parentheses.

* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

[35] Independent variables are taking values from 2007-2014, and control and dependent variables are taking values from 2010-2017, because of the 3-year lag.

Table XI reports the fixed effects model results of the number of patents/citations as the independent variable with its control variables on ROE as the firm performance measure for the full sample. As this model uses the same sample as the OLS regression for the full sample, the descriptive statistics are the same as reported in Table VII. The results of the other three performance measures are reported in Appendix E. The industry and country dummy variable are omitted due to the fact that dummy variables do not change over time. Year and firm fixed effects are taken into account.

Surprisingly, results of the fixed effects model show that both measures of green innovation are insignificant and extremely weak related to all four performance measures. ROS and Profit Margin show the highest *t*-values (1.19), but these still do not indicate a significant relationship. This is in line with previous studies as some studies argue that patents do not work in practice as well as they do in theory. Griliches, Hall, and Pakes (1991) and Arora et al. (2008), for example, find that patents have no influence on firm performance. A reason for this could be that patents could often be invented relatively cheaply, but the costs of holding on to these patents could be too high. Another reason could be that the goal of intention of patenting for many firms has evolved. Meaning that for a firm it is no longer the goal to protect their own innovation efforts to get a temporary monopoly to make abnormal profits, but rather to play a more strategic role in competitiveness. Firms could for example patent their innovations to block a competitor's innovation efforts (MacDonald, 2004). This means that many patents could have a defensive approach and therefore this forces many firms to patent inventions they normally would not and has no to almost no impact on firm performance.

These results doubt the value a patent has as a protection mechanism. They do repay some of the R&D expenditures, but the results indicate that there is no direct increase in the performance of the firm. The impact of a patent can vary greatly, with only a relative small number of patents having a significant impact on the performance of a firm.

6.2 Sample split by variable Size

The next robustness check is an OLS regression where the sample is split by the median of the variable size. Meaning that the full sample are now split into small and large firms. As described for the main analysis, the control variable size has strong correlations with all variables. But most importantly, the strong correlations with both measures of green innovation could affect the standard errors and thus the results could be incorrectly displayed as (in)significant. Therefore, it is interesting to check if there are any differences in results for both split samples.

Appendix F reports the descriptive statistics and correlation matrices of the split samples. The large firms show much higher means for all performance measures as they range for large firms from 6.73% for ROA to 12.20% for ROE and for small firms this range is only -2.62% for ROS to 3.83% for ROE. Also, the minima of the performance measures for large firms are around -5.00% and only for ROE this is -71.53%. These minima for small firms range from -146.85% for ROA to -260.37% for ROS. The maxima show similar results. Furthermore, there are also differences between the number of patents and citations between small and large firms. Large firms have an average of about 10 patents (12 citations) per firm year and this average for small firms is only 2.24 (1.49). The most patents (citations) in a firm year a small firm has is only 24 (26) and for large firms this is 166 (193). More than three-quarters of small firms does not have one citation. For large firms this is at least half of the firms. Moreover, of course the split samples differ in size as the mean for large firms is almost € 42 billion and for small firms this is only € 2 billion. Larger firms also are on average 20 years older and have a slightly higher average of leverage ratio.

The correlation matrices show that for small firms the proxy for the number of citations is not significant related to the four performance measures anymore. It also shows that for small firms the control variable firm size is not highly correlated with the measures of green innovation. However, this still is the case for large firms as it reports even stronger correlations between firm size and the green innovation measures compared to the main analysis.

OLS REGRESSION ROE < MEDIAN OF SIZE 2007 – 2014
Panel 1A

Model	1	2	3	4	5
Constant	-81.09 ***	-33.71 ***	-0.30	-34.08 ***	-81.04 ***
	(-9.04)	(-5.35)	(-0.10)	(-5.35)	(-9.01)
Log(PAT)		0.80	1.09	0.95	0.44
		(0.18)	(0.24)	(0.21)	(0.10)
Log(SIZE)	12.81 ***				12.81 ***
	(7.16)				(7.15)
Log(AGE)	6.72 *	21.61 ***		21.52 ***	6.72 *
	(1.67)	(6.07)		(6.02)	(1.67)
LEV	-0.05		0.09 ***	0.04	-0.05
	(-0.50)		(2.91)	(0.38)	(-0.49)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	20.086 ***	11.400 ***	2.232 *	9.137 ***	16.715 ***
Adj. R2	12.7%	6.0%	0.7%	5.8%	12.6%
Obs.	657	657	657	657	657

OLS REGRESSION ROE < MEDIAN OF SIZE 2007 – 2014
Panel 1B

Model	1	2	3	4	5
Constant	-81.09 ***	-32.26 ***	1.73	-32.58 ***	-79.64 ***
	(-9.04)	(-4.79)	(0.47)	(-4.80)	(-8.58)
Log(CIT)		0.25	0.44	0.27	0.24
		(0.63)	(1.05)	(0.68)	(0.62)
Log(SIZE)	12.81 ***				12.80 ***
	(7.16)				(7.15)
Log(AGE)	6.72 *	21.48 ***		21.36 ***	6.60
	(1.67)	(6.02)		(5.97)	(1.64)
LEV	-0.05		0.10	0.05	-0.05
	(-0.50)		(0.88)	(0.44)	(-0.42)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	20.086 ***	11.496 ***	2.498 **	9.225 ***	16.786 ***
Adj. R2	12.7%	6.0%	0.9%	5.9%	12.6%
Obs.	657	657	657	657	657

OLS REGRESSION ROE > MEDIAN OF SIZE 2007 – 2014
Panel 2A

Model	1	2	3	4	5
Constant	-7.49	19.22 ***	10.25 ***	23.08 ***	-18.31
	(-0.51)	(3.75)	(4.59)	(4.37)	(-1.16)
Log(PAT)		-1.56	-2.03	-1.53	-3.04 *
		(-1.02)	(-1.34)	(-1.01)	(-1.89)
Log(SIZE)	4.40 **				5.69 ***
	(2.28)				(2.79)
Log(AGE)	-7.74 ***	-6.78 **		-7.30 ***	-7.11 ***
	(-2.87)	(-2.48)		(2.68)	(-2.62)
LEV	-0.25 ***		-0.20 ***	-0.22 ***	-0.25 ***
	(-3.22)		(-2.69)	(-2.88)	(-3.32)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	8.999 ***	7.981 ***	8.262 ***	8.109 ***	8.124 ***
Adj. R2	5.7%	4.1%	4.2%	5.1%	6.1%
Obs.	657	657	657	657	657

OLS REGRESSION ROE > MEDIAN OF SIZE 2007 – 2014
Panel 2B

Model	1	2	3	4	5
Constant	-7.49	23.13 ***	13.38 ***	26.68 ***	3.61
	(-0.51)	(4.48)	(5.46)	(5.04)	(0.23)
Log(CIT)		0.61 ***	0.59 ***	0.58 ***	0.48 **
		(2.82)	(2.70)	(2.71)	(2.14)
Log(SIZE)	4.40 **				3.17
	(2.28)				(1.58)
Log(AGE)	-7.74 ***	-7.13 ***		-7.62 ***	-7.70 ***
	(-2.87)	(-2.64)		(-2.83)	(-2.86)
LEV	-0.25 ***		-0.19 **	-0.21 ***	-0.23 ***
	(-3.22)		(-2.58)	(-2.77)	(-3.02)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	8.999 ***	9.788 ***	9.699 ***	9.447 ***	8.306 ***
Adj. R2	5.7%	5.1%	5.0%	6.0%	6.3%
Obs.	657	657	657	657	657

Table XII: OLS regression results on ROE for split samples[36]. Log(PAT) is natural logarithm of the total number of granted green patents of the firm. Log(CIT) is the natural logarithm of the total number of citations of all granted green patents of the firm. Log(SIZE) is the natural logarithm of the net sales of the firm. Log(AGE) is the natural logarithm of the number of years since the date of incorporation of the firm. LEV is the ratio of long-term debt to total assets of the firm. Results are controlled for industry and country fixed effects. Panel 1 (2) reports the results of the regression for the small firms (large firms). Panel A (B) reports the results of the regression for the number of patents (citations) as the independent variable. T-values are reported in parentheses.

*	Statistical significance at the 10% level.
**	Statistical significance at the 5% level.
***	Statistical significance at the 1% level.

[36] Independent variables are taking values from 2007-2014, and control and dependent variables are taking values from 2010-2017, because of the 3-year lag.

Table XII reports the OLS regression results of the number of patents/citations as the independent variable with its control variables on ROE as the firm performance measure for the split samples. The results of the other three performance measures are reported in Appendix F.

For small firms the results report that both green innovation measures show positive signs with ROE, but these are insignificant in all models. Meaning that there is no relationship. For large firms the sign between the numbers of patents and ROE are negative but weak as only the full model is significant at 10%. However, using the number of citations as a measure of green innovation shows positive and significant relationships with ROE in all models at the 1% level for large firms, except for the full model (5). Although, the full model is significant at the 5% level. The results regarding the relationship between the number of patents and ROE for both small and large firms are similar to the results of the main analysis as it shows weak signs as well. For the number of citations only large firms match the results of the main analysis.

Regarding the other three measures of firm performance, small firms show the same signs as the results of the main analysis, only weaker. The most important difference for small firms is that the control variables firm size does not influence the relationship between the measures of green innovation and firm performance anymore. Meaning that the full models (5) show similar results as the other specific models (2, 3, and 4). For the main analysis the results of the relationship between green innovation and firm performance became negative and highly significant when the control variable firm size was taken into account. For small firms, the relationship between the number of patents and ROA, ROS, and Profit Margin is insignificant in all models, meaning that there is no relationship. Almost the same applies to the number of citations as it is insignificant in all models for all three performance measures except one. Although, this positive relationship between the number of citations and ROA is only significant at the 10% level. Mansfield (1986) finds that, although many economists believe that the protection a patent could bring tends to be more important to smaller firms, this proposition has little support as seven out of ten industries show no significance at all. This is in line with this study. However, the firms in the study of Mansfield (1986) are not that small as firms with sales below $ 25 million are not included in the sample.

Furthermore, the results of the sample consisting of large firms also show similar signs as the full sample, but also weaker and a bit more negative. For large firms, the relationship between the number of patents and ROA is still negative, but more significant. And for the relationship between the number of citations and ROA it is still positive, but no longer significant. The relationship between the number of patents and citations with both ROS and Profit Margin are negative in all models, but none of them show any significance.

To conclude, the results of the split samples show similar signs as the main analysis, only it lacks in significance. Both small and large firms show weaker signs than the main analysis, especially in the full models. However, for small firms the control variable firm size does not influence the relationship between green innovation and firm performance anymore, confirming that the control variable indeed has a huge impact on the sign and significance level of the relationship between green innovation and firm performance. Meaning that both the number of patents and citations do not have that much of an influence on the performance of a firm, but are influenced by the control variable firm size, which corresponds to the results of the fixed effects model.

6.3 2-Year lag

In this section, an OLS regression analysis with a 2-year lag sample is performed as the robustness check. Ernst (2001), for example, finds that national patents applications lead to a sales increase with a time-lag of two to three years after the priority year. As the main analysis already takes into account a 3-year lag, this test checks if the results of the sample with a 2-year lag are consistent or not. Based on the available data, the patents in the sample are from 2008 to 2014 as financial data from ORBIS is available for 2010-2017.

Appendix G reports the descriptive statistics and correlation matrix for the 2-year lag sample. The descriptive statistics for all variables of the 2-year lag sample are similar to the 3-year lag full sample. The only noteworthy difference between them is the decrease of observations from 1,314 to 1,134 firm years for the 2-year lag sample. This is due to the absence of the 180 firm years in 2007 that showed their impact in 2010 in the full sample. ORBIS has only financial data available from the year 2010, so the year 2007 is excluded from the sample. The correlation matrix for the 2-year lag sample only shows a small difference with the 3-year lag sample as the number of citations and ROE are not significant correlated anymore.

OLS REGRESSION ROE 2 YEAR LAG 2008 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-55.00	***	-17.52	***	3.88		-16.66	***	-58.88	***
	(-9.36)		(-4.12)		(1.74)		(-3.86)		(-9.57)	
Log(PAT)			0.72		1.39		0.75		-3.67	**
			(0.41)		(0.79)		(0.43)		(-2.10)	
Log(SIZE)	8.47	***							9.02	***
	(9.09)								(9.33)	
Log(AGE)	4.47	*	12.55	***			12.71	***	4.25	*
	(1.86)		(5.47)				(5.52)		(1.77)	
LEV	-0.22	***			-0.05		-0.08		-0.23	***
	(-3.01)				(-0.71)		(-1.08)		(-3.10)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	28.533	***	13.773	***	6.276	***	11.253	***	24.586	***
Adj. R2	10.7%		4.3%		1.8%		4.3%		11.0%	
Obs.	1134		1134		1134		1134		1134	

OLS REGRESSION ROE 2-YEAR LAG 2008 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-55.00	***	-14.93	***	6.30	**	-14.16	***	-55.88	***
	(-9.36)		(-3.37)		(2.52)		(-3.15)		(-8.72)	
Log(CIT)			0.48	**	0.55	**	0.47	*	-0.08	
			(1.97)		(2.27)		(1.95)		(-0.35)	
Log(SIZE)	8.47	***							8.56	***
	(9.09)								(8.86)	
Log(AGE)	4.47	*	12.33	***			12.49	***	4.43	*
	(1.86)		(5.38)				(5.44)		(1.85)	
LEV	-0.22	***			-0.05		-0.08		-0.23	***
	(-3.01)				(-0.66)		(-1.03)		(-3.03)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	28.533	***	14.744	***	7.428	***	12.010	***	23.780	***
Adj. R2	10.7%		4.6%		2.2%		4.6%		10.6%	
Obs.	1134		1134		1134		1134		1134	

Table XIII: OLS regression results on ROE for 2-year lag[37]. Log(PAT) is natural logarithm of the total number of granted green patents of the firm. Log(CIT) is the natural logarithm of the total number of citations of all granted green patents of the firm. Log(SIZE) is the natural logarithm of the net sales of the firm. Log(AGE) is the natural logarithm of the number of years since the date of incorporation of the firm. LEV is the ratio of long-term debt to total assets of the firm. Results are controlled for industry and country fixed effects. Panel A (B) reports the results of the regression for the number of patents (citations) as the independent variable. T-values are reported in parentheses.

* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

[37] Independent variables are taking values from 2008-2014, and control and dependent variables are taking values from 2010-2016, because of the 2-year lag.

Table XIII reports the OLS regression results of the number of patents/citations as the independent variable with its control variables on ROE as the firm performance measure for the 2-year lag sample. The results of the other three performance measures are reported in Appendix G.

As expected, the results show that the signs of the relationship between green innovation and ROE are similar to the main analysis in all models. Only, these signs are weaker for the 2-year lag results. The number of citations are now positive and significant at the 5% level in model (2) and (3) and only 10% in model (4) where this was significant at the 1% level for all three measures in the main analysis.

Regarding the other three firm performance measures, it also shows the same signs as the main analysis. For the relationship between the number of patents and ROA this negative sign is weaker and for the relationship between the number of citations and ROA this positive sign is stronger. Almost the same applies to ROS and Profit Margin. The relationship between number of patents and both performance measures show the same sign and significance. And the relationship between the number of citations and both performance measures show the same positive sign as well, but then more significant.

To conclude, the 2-year lag sample on the one hand shows slightly weaker results, but on the other hand shows slightly stronger results. Meaning that patents and its citations indeed show the same impact after 2 or 3 years and that there is no difference between these years, confirming previous literature (Ernst, 2001; Artz et al. 2010). However, one has to keep in mind that it is possible that patents and its citations do not have that big of an impact on the performance of a firm as the performances do not differ between the second and third year after introducing the patent.

6.4 Patent-sensitive industries

Because of the questionable impact of patents and its citations an OLS regression robustness check for a sample consisting of firms operating in only the patent-sensitive industries is performed. These industries are the industries described in paragraph 4.3.2. Therefore, the dummy variable Industry Control will not be added in the OLS regression analysis as all firms included in the sample are operating in patent-sensitive industries.

Previous studies find evidence for industries where the number of patents do have a significant impact on firm performance where other industries do not report any significance (Mansfield, 1986; Arora et al., 2003; MacDonald, 2004; Artz et al., 2010). Meaning that these industries are more sensitive towards granted patents. To repeat briefly, the firms in these patent-sensitive industries are operating in petroleum, machinery, fabricated metal products, pharmaceuticals, drugs and biotechnology, or chemical products.

Appendix H reports the descriptive statistics and correlation matrix for the sample consisting of only patent-sensitive industries. The means for the four performance measures are higher for the patent-sensitive industries compared to the full sample. Also, the patent-sensitive industries have on average more patents and citations than the other industries in the full sample. Moreover, regarding the correlation matrix, for patent-sensitive industries the number of citations is not significant correlated to all four performance measures anymore. This is not as expected, because it would have been more likely that the number of patents/citations of firms operating in these industries did indeed show a significant sign with the performance measures. However, for the main analysis the number of patents is negative correlated with all performance measures and for the patent-sensitive industry this correlation is positive for three out of four.

OLS REGRESSION ROE PATENT-SENSITIVE INDUSTRIES 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-23.06	***	11.43	*	13.24	***	10.06		-21.76	**
	(-2.88)		(1.83)		(5.16)		(1.58)		(-2.48)	
Log(PAT)			4.19	**	4.02	**	3.85	**	0.71	
			(2.22)		(2.13)		(2.02)		(0.36)	
Log(SIZE)	6.81	***							6.66	***
	(5.52)								(5.12)	
Log(AGE)	-4.92		1.92				1.82		-4.94	
	(-1.40)		(0.57)				(0.55)		(-1.40)	
LEV	-0.01				0.11		0.11		-0.01	
	(-0.11)				(1.15)		(1.14)		(-0.13)	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	8.412	***	1.941		2.277	*	1.779		6.744	***
Adj. R2	5.8%		0.6%		0.8%		0.6%		5.7%	
Obs.	480		480		480		480		480	

OLS REGRESSION ROE PATENT-SENSITIVE INDUSTRIES 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-23.06	***	12.95	*	14.66	***	11.47		-20.35	**
	(-2.88)		(1.94)		(4.91)		(1.70)		(-2.28)	
Log(CIT)			0.55	*	0.56	*	0.53	*	0.21	
			(1.79)		(1.86)		(1.72)		(0.69)	
Log(SIZE)	6.81	***							6.63	***
	(5.52)								(5.27)	
Log(AGE)	-4.92		1.97				1.78		-5.16	
	(-1.40)		(0.59)				(0.53)		(-1.46)	
LEV	-0.01				0.13		0.13		-0.01	
	(-0.11)				(1.42)		(1.39)		(-0.10)	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	8.412	***	1.359		1.917		1.505		6.817	***
Adj. R2	5.8%		0.2%		0.6%		0.4%		5.7%	
Obs.	480		480		480		480		480	

Table XIV: OLS regression results on ROE for patent-sensitive industries[38]. Log(PAT) is natural logarithm of the total number of granted green patents of the firm. Log(CIT) is the natural logarithm of the total number of citations of all granted green patents of the firm. Log(SIZE) is the natural logarithm of the net sales of the firm. Log(AGE) is the natural logarithm of the number of years since the date of incorporation of the firm. LEV is the ratio of long-term debt to total assets of the firm. Results are controlled for industry and country fixed effects. Panel A (B) reports the results of the regression for the number of patents (citations) as the independent variable. T-values are reported in parentheses.

* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

[38] Independent variables are taking values from 2007-2014, and control and dependent variables are taking values from 2010-2017, because of the 3-year lag.

Table XIV reports the OLS regression results of the number of patents/citations as the independent variable with its control variables on ROE as the firm performance measure for the sample consisting of patent-sensitive industries. The results of the other three performance measures are reported in Appendix H.

As expected, the relationship between the number of patents and ROE is positive and significant at the 5% level for all models except the full model (5). The positive sign of the relationship between the number of citations and ROE still remains, but is only significant at the 10% level instead of the 1% level the main analysis reports. Although, this could be due to the sample size. The positive and significant relationship between the number of patents and ROE confirms previous literature (Mansfield, 1986; Arora et al., 2003; MacDonald, 2004; Artz et al., 2010). The reason for these industries to be more important is due to the fact that firms within these industries generally do not prefer to rely on trade secret protection when patent protection is possible (Mansfield, 1986). Patents can often be invented relatively cheaply and the cost of upholding their validity or proving that the patent had been infringed upon is too high (Artz et al., 2010).

The other three performance measures show no significance at all for all models except the full model (5). In this model both the number of patents and citations is negatively and significantly related to ROA, ROS, and Profit Margin. However, probably the strong influence of control variable size on this relationship causes these results as this also happened with the main analysis.

To conclude, looking at the models (2), (3), and (4) that report specific combinations of variables, the relationship between the number of patents and firm performance is still positive, but stronger than the main analysis as it reports higher significance. This confirms previous literature that patents in these patent-sensitive industries indeed have a bigger impact on the performance of a firm than other industries (Mansfield, 1986; Arora et al., 2003; MacDonald, 2004; Artz et al., 2010). For citations this cannot be concluded as it shows similar results as the main analysis.

6.5 Firms with at least one citation

Another robustness check is an OLS regression with a sample consisting of firms that have granted green patents with at least one citation. It is arguable that the citations are a better indicator of green innovation than patents, because firms only continue to embroider on successful granted green patents.

Appendix I reports the descriptive statistics and correlation matrix for the sample consisting of firms with at least one citation. Again, the means of the performance measures of these firms lay higher than the full sample. Not surprisingly, the mean of the number of patents and citation are higher as well as the average number of patents a firm has that year almost doubled and the number of citations almost tripled compared to the full model. The firms with at least one citations are on average larger and older as well and report a slightly lower leverage ratio. Furthermore, looking at the correlation matrix, both measures of green innovation are now negative correlated with all four performance measures. For the number of patents the correlation with ROA, ROS, and Profit Margin is also significant.

OLS REGRESSION ROE >0 CITATIONS 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-31.69	***	11.25	*	12.80	***	13.02	*	-38.71	***
	(-3.39)		(1.66)		(3.76)		(1.88)		(-3.88)	
Log(PAT)			0.42		0.66		0.67		-4.21	*
			(0.20)		(0.31)		(0.31)		(-1.96)	
Log(SIZE)	8.90	***							8.83	***
	(6.60)								(6.90)	
Log(AGE)	-5.90		-0.05				-0.13		-6.00	*
	(-1.62)		(-0.01)				(-0.04)		(-1.66)	
LEV	-0.36	***			-0.13		-0.13		-0.36	***
	(-3.26)				(-1.20)		(-1.20)		(-3.29)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	10.708	***	1.941		2.308	*	1.842		9.626	***
Adj. R2	10.1%		0.9%		1.2%		1.0%		10.7%	
Obs.	435		435		435		435		435	

OLS REGRESSION ROE >0 CITATIONS 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-31.69	***	11.09		12.64	***	12.75		-36.10	***
	(-3.39)		(1.64)		(3.72)		(1.85)		(-3.71)	
Log(CIT)			0.14		0.27		0.27		-3.68	
			(0.06)		(0.11)		(0.12)		(-1.60)	
Log(SIZE)	8.90	***	-0.01						9.46	***
	(6.60)		(-0.00)						(6.80)	
Log(AGE)	-5.90				-0.13		-0.07		-5.99	*
	(-1.62)				(-1.18)		(-0.02)		(-1.65)	
LEV	-0.36	***					-0.13		-0.36	***
	(-3.26)						(-1.18)		(-3.32)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	10.708	***	1.932		2.286	*	1.825		9.381	***
Adj. R2	10.1%		0.9%		1.2%		0.9%		10.4%	
Obs.	435		435		435		435		435	

Table XV: OLS regression results on ROE for firms with at least one citation[39]. Log(PAT) is natural logarithm of the total number of granted green patents of the firm. Log(CIT) is the natural logarithm of the total number of citations of all granted green patents of the firm. Log(SIZE) is the natural logarithm of the net sales of the firm. Log(AGE) is the natural logarithm of the number of years since the date of incorporation of the firm. LEV is the ratio of long-term debt to total assets of the firm. Results are controlled for industry and country fixed effects. Panel A (B) reports the results of the regression for the number of patents (citations) as the independent variable. T-values are reported in parentheses.

* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

[39] Independent variables are taking values from 2007-2014, and control and dependent variables are taking values from 2010-2017, because of the 3-year lag.

Table XV reports the OLS regression results of the number of patents/citations as the independent variable with its control variables on ROE as the firm performance measure for the sample consisting of firms with at least one citation. The results of the other three performance measures are reported in Appendix I.

The relationship between green innovation and ROE as the performance measure is weak as it shows insignificant results in all but one model. Only the full model (5) of the relationship between the number of patents and ROE reports a negative sign that is significant at the 10% level. For this relationship these results are similar to the main analysis. However, for the relationship between the number of citations and ROE this is not as expected, because the main analysis reports positive signs that are significant at the 1% levels for the specific models (2), (3), and (4). For this robustness check there exist no relationship between the number of citations and ROE as all models show no significance.

Looking at the other three performance measures, the number of patents is negatively related to ROA, ROS, and Profit Margin in all models. Meaning that firms that have a granted green patent with at least one citation have a significant lower firm performance three years later, based on these three performance measures. This is somehow in contrast to the main analysis. Although, this positive impact the number of patents has on the performance measures in the full model could be influenced by firms having zero citations. Because, the 329 firm year observations of the quarter of the sample with the most granted green patents in a given year consists of 139 firm year observations with no citations. 82 out of the 139 report a higher mean than the mean of the full model for at least three out of four performance. However, regarding the negative relationship, DeCarolis and Deeds (1999) also find that patents are negatively and significantly related to firm performance. They argue that patent counts are an ambiguous measure subject to firm specific variations in the propensity of firms to patent given the resource expenditure required by the patent process. They name three arguments why the number of patents could be negatively related to firm performance. Firstly, although it is generally an accepted measure of innovation, the number of patents does not reflect the quality of it. Also, in some industries extensive patenting may be cost prohibitive. And lastly, some firms may be too young to have developed an extensive and reliable collection of patents to other firms. Patents do represent a stock of knowledge, but it seems that just simply using the number of patents is not a valid predictor of firm performance for all industries. Moreover, for the number of citations there exist no relationship with the other three performance measures in almost all models. For the specific models, the relationship between the number of citations and ROA is only significant at the 10% level in model (2). Although, in the full model (5) the relationship between the number of citations and ROA, ROS, and Profit Margin is negative and significant at the 1% level. But again, this is because of the control variable size.

To conclude, for firms with at least one citation the robustness tests reports a negative and significant signs for the relationship between the number of patents and firm performance for the majority of models. This is contrary to the main analysis.

6.6 2-Year and 3-year lag for Firm Performance Improvement

Another measure of the dependent variable is also used as a robustness check. Some studies argue whether to use the value of firm performance indicators at a specific time after the green patent was granted, like this study uses a lag of three years in the main analysis, or to use the improvement of the value of these firm performance indicators from the moment the green patent was granted to a specific year. Aguilera-Caracuel and Ortiz-de-Mandojana (2013) are an example of the latter. They use firm financial performance improvement as their dependent variable and measure the improvement by calculating the firm performance measure for two and three consecutive years and this change is expressed as a percentage. Their independent variable is the same as this study, namely the number of granted green patents a firm has for a given year. Another study that uses firm performance improvement is the one of Cho and Pucik (2005). They measure it as the three-year average of their profitability ratios. This study follows the same approach as these two studies and calculate the average firm performance improvement over two and three years.

Appendix J reports the descriptive statistics and correlation matrix for the sample using firm performance improvement as the dependent variable. Of course, the descriptive statistics of the measurements of firm performance improvement are much more spread out than the firm performance measures used in the main analysis. On average all firms have an increase in their firm performance improvement between 14.90% for ROA and 19.64% for ROS after two years and between 28.32% for ROA and 34.00% for Profit Margin after three years. Moreover, the correlation matrices show that the number of citations are not positive and significant related to the dependent variables anymore. In fact, both the number of patents and citations are negatively correlated to almost all measures of firm performance improvement after two and three years, except for the correlation between the number of patents and the improvement of ROE.

OLS REGRESSION ROE IMPROVEMENT YEAR 2 2010 – 2014
Panel 1A

Model	1	2	3	4	5
Constant	-19.61	-11.81	7.64	-21.73	-11.97
	(-0.32)	(-0.19)	(0.13)	(-0.49)	(-0.19)
Log(PAT)		7.54	6.24	6.12	7.13
		(0.44)	(0.36)	(0.37)	(0.41)
Log(SIZE)	-1.01	-3.16	2.37		-2.11
	(-0.11)	(-0.33)	(0.26)		(-0.21)
Log(AGE)	28.47	29.68		26.79	28.93
	(1.13)	(1.18)		(1.15)	(1.14)
LEV	-0.40		-0.43	-0.41	-0.38
	(-0.53)		(-0.58)	(-0.57)	(-0.51)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	0.351	0.332	0.123	0.375	0.320
Adj. R2	0.0%	0.0%	0.0%	0.0%	0.0%
Obs.	811	811	811	811	811

OLS REGRESSION ROE IMPROVEMENT YEAR 2 2010 – 2014
Panel 1B

Model	1	2	3	4	5
Constant	-19.61	-75.74	-60.27	-53.31	-77.11
	(-0.32)	(-1.15)	(-0.95)	(-1.17)	(-1.17)
Log(CIT)		-5.14 **	-5.43 **	-4.97 **	-5.31 **
		(-2.14)	(-2.25)	(-2.15)	(-2.20)
Log(SIZE)	-1.01	3.35	8.91		4.93
	(-0.11)	(0.35)	(0.99)		(0.50)
Log(AGE)	28.47	26.74		30.66	25.63
	(1.13)	(1.06)		(1.33)	(1.02)
LEV	-0.40		-0.59	-0.46	-0.54
	(-0.53)		(-0.80)	(-0.64)	(-0.73)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	0.351	1.213	1.113	1.371	1.100
Adj. R2	0.0%	0.1%	0.1%	0.2%	0.1%
Obs.	811	811	811	811	811

OLS REGRESSION ROE IMPROVEMENT YEAR 3 2010 – 2014
Panel 2A

Model	1		2		3		4		5	
Constant	-57.37		-44.27		-30.82		2.37		-45.31	
	(-0.96)		(-0.71)		(-0.52)		(0.05)		(-0.72)	
Log(PAT)			14.18		10.97		16.66		11.54	
			(0.83)		(0.64)		(1.01)		(0.67)	
Log(SIZE)	12.34		6.57		12.53				10.57	
	(1.33)		(0.70)		(1.53)				(1.10)	
Log(AGE)	19.10		23.24				31.19		19.85	
	(0.74)		(0.90)				(1.32)		(0.77)	
LEV	-1.44	**			-1.44	**	-1.23	*	-1.40	*
	(-2.02)				(-2.01)		(-1.76)		(-1.96)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	1.390		0.713		1.363		1.240		1.233	
Adj. R2	0.2%		0.0%		0.2%		0.1%		0.2%	
Obs.	811		811		811		811		811	

OLS REGRESSION ROE IMPROVEMENT YEAR 3 2010 – 2014
Panel 2B

Model	1		2		3		4		5	
Constant	-57.37		-98.27		-90.75		-21.81		-102.57	
	(-0.96)		(-1.51)		(-1.45)		(-0.47)		(-1.58)	
Log(CIT)			-3.63		-4.29	*	-3.04		-4.21	*
			(-1.53)		(-1.80)		(-1.33)		(-1.77)	
Log(SIZE)	12.34		12.40		19.58	**			17.07	*
	(1.33)		(1.31)		(2.22)				(1.77)	
Log(AGE)	19.10		20.64				35.10		16.72	
	(0.74)		(0.80)				(1.48)		(0.65)	
LEV	-1.44	**			-1.61	**	-1.30	*	-1.58	**
	(-2.02)				(-2.25)		(-1.85)		(-2.20)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	1.390		1.044		1.936	*	1.388		1.682	
Adj. R2	0.2%		0.0%		0.6%		0.2%		0.5%	
Obs.	811		811		811		811		811	

Table XVI: OLS regression results on ROE improvement[40]. Log(PAT) is natural logarithm of the total number of granted green patents of the firm. Log(CIT) is the natural logarithm of the total number of citations of all granted green patents of the firm. Log(SIZE) is the natural logarithm of the net sales of the firm. Log(AGE) is the natural logarithm of the number of years since the date of incorporation of the firm. LEV is the ratio of long-term debt to total assets of the firm. Results are controlled for industry and country fixed effects. Panel 1 (2) reports the results of the regression after two (three) years. Panel A (B) reports the results of the regression for the number of patents (citations) as the independent variable. T-values are reported in parentheses.

* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

[40] In panel A independent variables are taking values from 2010-2014, and control and dependent variables are taking values from 2012-2016, because of the 2-year lag. In panel B independent variables are taking values from 2010-2014, and control and dependent variables are taking values from 2013-2017, because of the 3-year lag.

Table XVI reports the OLS regression results of the number of patents/citations as the independent variable with its control variables on the improvement of ROE after two and three years. The results of the other three performance measures are reported in Appendix J.

The relationship between the number of patents and the improvement of ROE is positive in all models, only it lacks of any significance. For the relationship between the number of citations and the improvement of ROE this is negative and significant at the 5% level after two years and only significant at the 10% level for model (3) and (5) after three years. For the first relationship this is similar to the main analysis, but for the second this is not as it showed positive and significant signs.

Regarding the other three firm performance improvement measures, the relationship between the number of patents and the improvement of ROA, ROS, and Profit Margin after two and three years is negative in all models, but again it does not show any significance, meaning that there exist no relationship. After two years, the relationship between the number of citations and the improvement of ROA, ROS, and Profit Margin is negative in all models at the 10%, but after three years this relationship becomes insignificant for ROA, significant at the 5% for ROS in model (2), (3), and (5) and Profit Margin for model (2) and (5). Aguilera-Caracuel and Ortiz-de-Mandojana (2013) also come to this conclusion as they fail to find any evidence of the improvement of firm performance. They find that after two years the improvement of firm performance is negatively related with green innovation, which is significant at the 10% level. After three years this relationship is positive, but lacks significance. However, this could indicate a turnaround. They name two reasons why it could be that green firms do not experience a higher improvement of firm performance. Firstly, the impact of green innovations could require time to materialize and secondly, all green innovative firms cannot have the necessary conditions to obtain an improvement in their performance.

To conclude, using firm performance improvement as the dependent variable does not change that much for the number of patents. However, the number of citations as the green innovation indicator has a negative impact on the improvement of firm performance after both two and three years.

6.7 Citation Dummy

The last robustness check replaces of the number of citations as the independent variable with a citation dummy, because of the non-normal distribution of the number of citations in the main analysis. As this model uses the same sample as the OLS regression for the full sample, the descriptive statistics are the same as reported in Table VII.

Appendix K reports the correlation matrix of the sample using a citation dummy. Only the correlation between the alternative independent variable and other variables differ from the correlation matrix of the full model, because the number of citations is the only replaced variable. The only notable difference is that the correlation between the two independent variables became stronger as the correlation between the number of patents and citations is 0.206 and the correlation between the number of patents and the citation dummy is 0.249. Although this difference is small, it means that a citation dummy is more in line with the number of patents as the other measure of green innovation.

OLS REGRESSION ROE CITATION DUMMY 2007 – 2014

Model	1		2		3		4		5	
Constant	-49.84	***	-17.04	***	2.45		-16.68	***	-49.22	***
	(-8.74)		(-3.97)		(1.17)		(-3.83)		(-8.55)	
Citation Dummy			4.62	***	5.24	***	4.59	***	1.28	
			(2.82)		(3.18)		(2.81)		(0.78)	
Log(SIZE)	7.85	***							7.68	***
	(8.82)								(8.38)	
Log(AGE)	3.70		11.79	***			11.85	***	3.75	
	(1.48)		(4.98)				(5.00)		(1.50)	
LEV	-0.17	**			-0.01		-0.03		-0.17	**
	(-2.45)				(-0.20)		(-0.48)		(-2.38)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	26.546	***	14.983	***	8.630	***	12.025	***	22.217	***
Adj. R2	8.9%		4.1%		2.3%		4.0%		8.8%	
Obs.	1314		1314		1314		1314		1314	

Table XVII: OLS regression results on ROE using a citation dummy[41]. The Citation Dummy takes the value of 1 if the firm has at least one citation and zero otherwise. Log(SIZE) is the natural logarithm of the net sales of the firm. Log(AGE) is the natural logarithm of the number of years since the date of incorporation of the firm. LEV is the ratio of long-term debt to total assets of the firm. Results are controlled for industry and country fixed effects. T-values are reported in parentheses.

* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

[41] Independent variables are taking values from 2007-2014, and control and dependent variables are taking values from 2010-2017, because of the 3-year lag.

Table XVII reports the OLS regression results with a sample using a citation dummy as the replacement of the number of citations with its control variables on ROE as the firm performance measure. The results of the other three performance measures are reported in Appendix K.

The results of this robustness check show the same results as the main analysis. Even the same signs with the same level of significance are founded in almost all models. The only small difference is that the relationship between the citation dummy and ROA is more significant in model (2), (3), and (4) as it shows a significance level of 5%, 10%, and 5% respectively. To conclude, a citation dummy has a higher correlation to the number of patents than the number of citations, but the results of this robustness check are not different from the main analysis.

7 CONCLUSION

7.1 Conclusion

The intention of this study is to investigate the impact of green innovation on firm performance and to provide concrete suggestions for the field of study. It uses an unbalanced panel dataset and the sample consists of 450 unique firms with at least one European granted green patent in one of the total 1,314 firm year observations between the years 2007 and 2014. These firms have a combined number of 7,700 newly European green patents granted by EPO with its 9,087 citations. In this chapter an answer will be given to the research question: "To what extent does green innovation influence firm financial performance?". An OLS regression analysis is used to find supporting evidence for the hypothesis: "green innovation affects firm financial performance positively". This regression uses the number of patents and citations as proxies of green innovation, ROE, ROA, ROS, and Profit Margin as measures of firm performance, and firm size, firm age, firm leverage, and two industry and country dummies as control variables. This study contributes to the literature of innovation by going deeper into the green part of it, by adding new empirical evidence to green innovation based on the use of panel data instead of survey data, and by not making a distinction between the four parts of innovation and thus not focusing on green product innovation alone. The hypothesis only receives partial support.

Literature elaborates four theories that explain the relationship between (green) innovation and the performance of a firm. The innovation theory of Schumpeter describes that firms that try new ways of using its knowledge, technology and resources bring more opportunities that could lead to a stronger market position. These relatively more adaptable firms are more likely to outperform firms that do not. The resource-based view is based on this as it defines that firms must identify its potential key resources that are valuable, rare, not imitable and not substitutable, because the performance of a firm results from these kind of resources. Green innovation is such a unique capability and thus a key driver of firm performance. Although, there is no best way to organize or lead a firm. The process of decision making differs across firms, but the impact of the same decisions also differ across firms, which is described by the contingency theory. This theory names three types of factors and this study focuses on the response and performance factor, because a firm can influence these two. Firms use green innovation to increase the performance of their firm. However, the institutional theory argues that practices could also be adopted due to non-efficiency to gain legitimacy whether or not the practices may lead to a performance increase. Based on these theories and on empirical evidence, the hypothesis of this study predicts a positive relationship between green innovation and firm performance.

The OLS regression for the main analysis shows that both proxies for green innovation indeed show the positive sign with ROE as the firm performance measure. For the number of citations there is also a relationship with ROE as this sign is statistically significant at the 1% level. However, looking at ROA as the performance measure, the number of citations still shows a positive and significant sign, but for the number of patents it becomes negative and even significant at the 5% level for some models. For ROS and Profit Margin as the performance measures the regression reports extremely weak results and almost no significance at all for both proxies of green innovation, meaning that there is no relationship. This given and the different results could indicate that having only one does not have that big of an impact on the performance of a firm. Furthermore, looking at the regression models where the control variable firm size is included as well, the regression analysis mostly reports negative and significant results. Meaning that for larger firms the more European granted green patents/citations a firm has, the lower its performance. Although, the high correlation between firm size and the two proxies of green innovation could influence this relationship strongly and incorrectly. With these mixed results the hypothesis only receives partial support.

Robustness checks also report mixed results. The fixed effects model regression report insignificant and extremely weak results for the hypothesis in all models. The OLS regression using two samples split by the median of firm size show similar results as the main analysis, only it lacks in significance as well. This is especially the case in the full models, implying that the control variable firm size indeed has a huge impact on the relationship between green innovation and firm performance. Using a 2-year lag instead of a 3-year lag also reports similar results. However, using a sample consisting of firms only operating in patent-sensitive industries, the results are still positive, but stronger than the main analysis. And using a sample consisting of firms with at least one citation the relationship between the number of patents and firm performance seems to be more negative than the main analysis. This is also the case when firm performance improvement is used as the measurement of firm performance, but then for the relationship between the number of citations and firm performance. Moreover, the results of using a citation dummy to replace the number of citations as the measure of green innovation show no differences with the main analysis. These mixed results indicate that the results of the main analysis are not consistent, not robust and do not provide reliable outcomes.

The positive findings prove that the positive effects green innovation, such as reducing pollution and limiting hazardous and toxic waste and thus reducing the cost of disposal and improving the green efficiency and response to external environmental pressure from customers, all ultimately contribute to a better firm performance. This is in line with the four theories. Green innovation is one of the creative ways described by Schumpeter (1934) to outperform their competitive environment. Because, green innovations needs valuable resources that are difficult to obtain and hard to imitate or trade and this could lead to a relatively better performance of a firm compared to its competitors. This is still the case nowadays as the more successful granted green patents show a higher firm performance. Because, the number of citations clarifies the number of other firms that are trying to copy or improve that granted green patent and could thus arguably be a measure of its success. Green innovation encourages the use of raw materials efficiently and this could results in lower costs and new ways of converting waste into saleable products.

However, the insignificant results of some robustness checks indicate that patents do not work in practice as well as they do in theory. Reasons are that patents could often be invented relatively cheaply, but the costs of holding on to these could be too high or firms could have evolved patenting goals as some firms do not apply for a patent to protect their own innovation efforts to get a temporary monopoly to make abnormal profits, but rather to play a more strategic role in competitiveness. This means that firms will not protect all of its invented patents, because the protection could be too costly and therefore they keep on filing new patents without safeguarding old ones. These results doubt the value a patent has as a protection mechanism. They do repay some of the R&D expenditures, but the insignificant results indicate that there is no direct increase in the performance of the firm. Firms could for example patent their innovations to block a competitor's innovation efforts (MacDonald, 2004). This means that many patents could have a defensive approach and therefore this forces many firms to patent inventions they normally would not and has no to almost no impact on firm performance. Although, this is not the case for all industries. Patents do still have a positive impact on the performance of a firm for firms operating in patent-sensitive industries. In such industries the protection of patents is more essential than in other industries, because firms within these industries generally do not prefer to rely on trade secret protection when patent protection is possible (Mansfield, 1986).

Contrary, the negative results indicate that the number of patents does not reflect the quality of it, that extensive patenting may be cost prohibitive and that some firms may be too young to have developed an extensive and reliable collection of patents to other firms. Patents do represent a stock of knowledge, but it seems that just simply using the number of patents is not a valid predictor of firm performance for all industries.

7.2 Limitations and further research

Overall, these mixed results make it hard to make any reliable and substantiated suggestions for the field of study. So, this study has some limitations that need to be considered. Both the main analysis and robustness checks have mixed results, indicating that using the number of patents and citations are not sufficient measures of green innovation. Thus, the first limitation of this study is that it simply uses the number of patents and citations as proxies of green innovation. Although, using patent and citation counts are generally accepted as one of the most appropriate indicators of innovation, this measure only indicates the quantity of patenting activity and not the impact of these patents. Other studies already mention the inability of distinguishing between high and low-impact patents (Trajtenberg, 1990; Hall et al., 2001). Looking at the positive results of the robustness check using a sample consisting of firms operating in patent-sensitive industries, further research should examine the role of green patent impact in these industries as higher patent impact could mitigate some of the negative effects found in other analyses in this study. Also, a recommendation for another measure of green innovation is an average or cumulative patent growth over a couple of years and taking the average of firm performance over two and/or three years as the measure of firm performance. This study tried to look into this measure, but the sample size decreased to a total of 64 unique firms, which is not enough to perform a reliable analysis.

Another limitation is that this study only looks at the direct relationship between green innovation and firm performance. However, there could also be an indirect impact on this relationship. This third factor could be a moderator or mediator and it changes the strength or direction of the effect of the direct relationship. A recommendation for a moderator in this field of study is environmental dynamism. This third factor refers to frequent and rapid changes induces by technology, customers, and suppliers. Managers should consider these changes when designing green innovations in a dynamic environment (Lin et al., 2013). Another recommendation for a mediator is product announcements. Artz et al. (2010) do not found any significant evidence for the direct relationship between the number of patents and firm performance. However, they do find positive and significant relationships between the number of patents and product announcements and between product announcements and firm performance. Indicating that product announcement indeed mediates the direct relationship. This mediator represents product innovation efforts by a firm. These announcements could be introductions, reviews, previews, or announcements of a new product or service. Although it does not represent all four parts of innovation, it does represent the largest part.

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9 APPENDIX

9.1 Appendix A – Overview of factors within the field of study

Dependent Variable	Literature	Method	Sample	Period	Data collection method	Measurement of variable	Adapted from
Firm Performance	Ar (2012)	SEM	The largest 1000 exporters explained by Turkish Exporters Assembly (TEA) for 2010	June 2011 – August 2011	Questionnaire	7-point Likert Scale	Eiadat et al., 2011
	Lin. Kim-Hua. and Geng (2013)	Regression Analysis	Vietnam motorcycle industry	January 2011 – July 2011	Survey	5-point Likert Scale	Li et al., 2010
	Chan. Yee. Dai. and Lim (2016)	SEM	The industry operating in China	April 2015 – May 2015	Survey	7-point Likert Scale	Staw & Epstein, 2000; Kaynak & Hartley, 2008
	Aguilera-Caracuel and Ortiz-de-Mandojana (2013)	Matched-pairs analysis	88 green innovative firms and a matched-pairs sample of 70 pairs of green innovative and non–green innovative firms	1993-2013	EPO. GPI. CGD. ESI	ROA	-
	Li et al. (2010)	SEM	Chinese firms	-	Survey	7-point Likert Scale	Li & Atuahene-Gima, 2001
	Vithessonthi and Racela (2016)	OLS	Chinese listed manufacturing firms	1990-2013	Datastream	ROA. ROS. Tobin’s Q. Annual Stock Returns	-
	Abuhommous (2017)	OLS	Listed firm on the Amman Stock Exchange	1999-2015	Osiris. Central Bank of Jordan.	ROA	-
	Kale. Reis. and Venkateswaran. (2009)	OLS	S&P 500. S&P mid-cap 400. and S&P smallcap 600 firms	1993-2004	(S&P) ExecuComp database	ROA. ROE. Tobin’s Q	-

	Ilyukhin (2015)	OLS. Fixed/Random effects model	Russian joint-stock firms	2004-2013	Bureau van Dijk's Ruslana dataset	ROA. ROE. Tobin's Q. Profit Margin	-
	Frijns. Dodd. and Cimerova (2016)	OLS	Large British firms	2002-2014	Datastream	ROA. Tobin's Q	-
	Gui-long. Yi. Kai-hua. and Jiang (2017)	OLS. Quantile Regression	China's top 100 domestic electronics manufacturing firms	2003-2007	China's Ministry of Industry and Information Technology	ROA. ROE	-
	Ibhagui and Olokoyo (2018)	Threshold regression model	Listed firms in Nigeria	2003-2007	Nigerian Stock Exchange (NSE) Factbook and the published annual reports	ROA. Tobin's Q	-
Business Performance	Kober. Subraamanniam. and Watson (2011)	Categorial regression	Australian SMEs	1995-1998	Australian Bureau of Statistics	ROE. Total Revenue	-
	Pramod. Krishnan. and Puja (2012)	OLS. Fixed/Random effects model	Indian manufacturing sector	2001-2010	Prowess database of CMIE	Tobin's Q	-
	Andras and Srinivasan (2003)	OLS. GLS	Consumer product and manufacturing product firms	2000	COMPUSTAT database	Profit Margin. Profitability	-
	Anagnostopoulou and Levis (2008)	OLS	UK listed non-financial firms	1990-2003	London Share Price Database	Profit Margin. Revenue Growth. Gross Income	-
	Aggelopoulos. Eriotis. Georgopoulos. and Tsamis (2016)	OLS	Greek SMEs	2002-2007	Hellastat database	Profit Margin. Revenue Growth	-

	Oke. Burke. and Myers (2007)	Regression analysis	UK SMEs	-	Survey	Sales turnover growth. net profit growth before tax	Griffin, 1997; Goffin & Pfeiffer, 1999; Avlonitis et al., 2001; Oke, 2002; 2004
Innovation Performance	Oke. Burke. and Myers (2007)	Regression analysis	UK SMEs	-	Survey	7-point Likert Scale	Griffin, 1997; Goffin & Pfeiffer, 1999; Avlonitis et al., 2001; Oke, 2002; 2004
Competitive Advantage	Chen. Lai and Wen (2006)	SEM	Corporations in information and electronics industries in Taiwan	-	Survey	5-point Likert Scale	-
Competitive Advantage	Gürlek and Tuna (2018)	SEM	Four- and five-star hotel firms in Antalya	-	Questionnaire	7-point Likert Scale	Chang, 2011
Competitive Capability	Chiou. Chan. Lettice. and Chung (2011)	SEM	Firms in Taiwan	-	Survey	5-point Likert Scale	Rao, 2002; Rao & Holt, 2005
	Ar (2012)	SEM	The largest 1000 exporters explained by Turkish Exporters Assembly (TEA) for 2010	June 2011 – August 2011	Questionnaire	7-point Likert Scale	Tang, 2006
Cost Efficiency	Chan. Yee. Dai. and Lim (2016)	SEM	The industry operating in China	April 2015 – May 2015	Survey	7-point Likert Scale	Wong et al., 2011; Gligor et al., 2015
Green Product Innovation Performance	Chang (2016)	SEM	Taiwanese manufacturing industry	2012	Survey	5-point Likert Scale	Chen et al., 2006; Chang, 2011
Environmental Performance	Chiou. Chan. Lettice. and Chung (2011)	SEM	Firms in Taiwan	-	Survey	5-point Likert Scale	Rao, 2002; Rao & Holt, 2005

Independent Variable	Literature	Measurement Model	Sample	Period	Data collection method	Measurement of variable	Adapted from
Green Product Innovation	Chen. Lai and Wen (2006)	SEM	Corporations in information and electronics industries in Taiwan	-	Survey	5-point Likert Scale	-
Green Product Innovation	Ar (2012)	SEM	The largest 1000 exporters explained by Turkish Exporters Assembly (TEA) for 2010	June 2011 – August 2011	Questionnaire	7-point Likert scale	Chiou et al., 2011
	Lin. Kim-Hua. and Geng (2013)	Regression Analysis	Vietnam motorcycle industry	January 2011 – July 2011	Survey	5-point Likert Scale	Zhu & Sarkis, 2004; Triebswetter & Wackerbauer, 2008; Tseng et al., 2009; Awasthi et al., 2010; Li et al., 2010; Chiou et al., 2011
	Chan. Yee. Dai. and Lim (2016)	SEM	The industry operating in China	April 2015 – May 2015	Survey	7-point Likert Scale	Chen et al., 2006; Chen, 2008; Chiou et al., 2011
	Chiou. Chan. Lettice. and Chung (2011)	SEM	Firms in Taiwan	-	Survey	5-point Likert Scale	Chen et al., 2006; Chen, 2008
	Chen. Lai and Wen (2006)	SEM	Corporations in information and electronics industries in Taiwan	-	Survey	5-point Likert Scale	-
Green Process Innovation	Chiou. Chan. Lettice. and Chung (2011)	SEM	Firms in Taiwan	-	Survey	5-point Likert Scale	Chen et al., 2006; Chen, 2008

Green Managerial/Method Innovation	Chiou. Chan. Lettice. and Chung (2011)	SEM	Firms in Taiwan	-	Survey	5-point Likert Scale	Chen et al., 2006; Chen, 2008
Product Innovation	Li et al. (2010)	SEM	Chinese firms	-	Survey	7-point Likert Scale	Roberts, 1999; Chandy & Tellis, 2000
	Oke. Burke. and Myers (2007)	Paired sample t-test	UK SMEs	-	Survey	7-point Likert Scale	Griffin, 1997; Goffin & Pfeiffer, 1999; Avlonitis et al., 2001; Oke, 2002; 2004
Process Innovation	Oke. Burke. and Myers (2007)	Paired sample t-test	UK SMEs	-	Survey	7-point Likert Scale	Griffin, 1997; Goffin & Pfeiffer, 1999; Avlonitis et al., 2001; Oke, 2002; 2004
Service Innovation	Oke. Burke. and Myers (2007)	Paired sample t-test	UK SMEs	-	Survey	7-point Likert Scale	Griffin, 1997; Goffin & Pfeiffer, 1999; Avlonitis et al., 2001; Oke, 2002; 2004
Green Innovation	Gürlek and Tuna (2018)	SEM	Four- and five-star hotel firms in Antalya	-	Questionnaire	7-point Likert Scale	Chen et al., 2006
	Aguilera-Caracuel and Ortiz-de-Mandojana (2013)	Matched-pairs analysis	88 green innovative firms and a matched-pairs sample of 70 pairs of green innovative and non–green innovative firms	1993-2013	EPO. GPI. CGD. ESI	Green Patents / Total Patens × 100%	-
	Chiou. Chan. Lettice. and Chung (2011)	SEM	Firms in Taiwan	-	Survey	5-point Likert Scale	Chen et al., 2006; Chen, 2008

	Chiou. Chan. Lettice. and Chung (2011)	SEM	Firms in Taiwan	-	Survey	5-point Likert Scale	Chen et al., 2006; Chen, 2008
Non-Green Innovation	Aguilera-Caracuel and Ortiz-de-Mandojana (2013)	Matched-pairs analysis	88 green innovative firms and a matched-pairs sample of 70 pairs of green innovative and non–green innovative firms	1993-2013	EPO. GPI. CGD. ESI	Non-Green Patents / Total Patens × 100%	-

Antecedent Variable	**Literature**	**Method**	**Sample**	**Period**	**Data collection method**	**Measurement of variable**	**Adapted from**
Green Organizational Culture	Gürlek and Tuna (2018)	SEM	Four- and five-star hotel firms in Antalya	-	Questionnaire	7-point Likert Scale	Marshall et al., 2015
Market Demand	Lin. Kim-Hua. and Geng (2013)	Regression Analysis	Vietnam motorcycle industry	January 2011 – July 2011	Survey	5-point Likert Scale	Kammerer, 2009; Oltra & Jean, 2009
Pressure of Environmental Regulations / Policies	Chan. Yee. Dai. and Lim (2016)	SEM	The industry operating in China	April 2015 – May 2015	Survey	7-point Likert Scale	Zhu et al., 2011
Corporate Environmental Commitment	Chang (2016)	SEM	Taiwanese manufacturing industry	2012	Survey	5-point Likert Scale	Henriques & Sadorsky, 1999
Greening The Supplier	Chiou. Chan. Lettice. and Chung (2011)	SEM	Firms in Taiwan	-	Survey	5-point Likert Scale	Rao, 2002; Rao & Holt, 2005

Moderating Variable	Literature	Method	Sample	Period	Data collection method	Measurement of variable	Adapted from
Managerial environmental concern	Ar (2012)	SEM	The largest 1000 exporters explained by Turkish Exporters Assembly (TEA) for 2010	June 2011 – August 2011	Questionnaire	7-point Likert scale	Eiadat et al., 2011
	Chiou. Chan. Lettice. and Chung (2011)	SEM	Firms in Taiwan	-	Survey	5-point Likert Scale	-
Environmental Dynamism	Chan. Yee. Dai. and Lim (2016)	SEM	The industry operating in China	April 2015 – May 2015	Survey	7-point Likert Scale	Azadegan et al., 2013
Stringent Environmental Regulations	Aguilera-Caracuel and Ortiz-de-Mandojana (2013)	Multiple and moderated regression analysis	88 green innovative firms and a matched-pairs sample of 70 pairs of green innovative and non–green innovative firms	1993-2013	EPO. GPI. CGD. ESI	Questions 1101 – 1111 of the ESI 2005	-
Environmental normative levels	Aguilera-Caracuel and Ortiz-de-Mandojana (2013)	Multiple and moderated regression analysis	88 green innovative firms and a matched-pairs sample of 70 pairs of green innovative and non–green innovative firms	1993-2013	EPO. GPI. CGD. ESI	Two sets of rank percentiles	-
Control Variable	**Literature**	**Method**	**Sample**	**Period**	**Data collection method**	**Measurement of variable**	**Adapted from**
Firm Age	Chen. Lai and Wen (2006)	SEM	Corporations in information and electronics industries in Taiwan	-	Survey	The years of the firm founded	-
	Oke. Burke. and Myers (2007)	Regression analysis	UK SMEs	-	Survey	Age since SMEs have been in business	-

	Chen. Lai and Wen (2006)	SEM	Corporations in information and electronics industries in Taiwan	-	Survey	Number of employees	-
Firm Size	Aguilera-Caracuel and Ortiz-de-Mandojana (2013)	Multiple and moderated regression analysis	88 green innovative firms and a matched-pairs sample of 70 pairs of green innovative and non–green innovative firms	1993-2013	EPO. GPI. CGD. ESI	Total net revenues	-
	Li et al. (2010)	SEM	Chinese firms	-	Survey	-	-
	Anagnostopoulou and Levis (2008)	OLS	UK listed non-financial firms	1990-2003	London Share Price Database		-
	Kale. Reis. and Venkateswaran. (2009)	OLS	S&P 500. S&P mid-cap 400. and S&P smallcap 600 firms	1993-2004	(S&P) ExecuComp database		-
Firm Leverage	Pramod. Krishnan. and Puja (2012)	OLS. Fixed/Random effects model	Indian manufacturing sector	2001-2010	Prowess database of CMIE	Total debt / Total assets	-
	Frijns. Dodd. and Cimerova (2016)	OLS	Large British firms	2002-2014	Datastream	Total debt / Total assets	-
	Vithessonthi and Racela (2016)	OLS	Chinese listed manufacturing firms	1990-2013	Datastream	Total debt / Total assets	-
	Abuhommous (2017)	OLS	Listed firm on the Amman Stock Exchange	1999-2015	Osiris. Central Bank of Jordan	Total debt / Total assets	-
	Chen. Leung. and Evans (2018)	OLS	-	1998-2006	CRSP. NBER patent database	Total debt / Total assets	-

Type of Industry	Aguilera-Caracuel and Ortiz-de-Mandojana (2013)	Multiple and moderated regression analysis	88 green innovative firms and a matched-pairs sample of 70 pairs of green innovative and non–green innovative firms	1993-2013	EPO. GPI. CGD. ESI	Four different industries	-
Firm level of Innovation	Aguilera-Caracuel and Ortiz-de-Mandojana (2013)	Multiple and moderated regression analysis	88 green innovative firms and a matched-pairs sample of 70 pairs of green innovative and non–green innovative firms	1993-2013	EPO. GPI. CGD. ESI	Total number of patents registered	-
Prior financial performance	Aguilera-Caracuel and Ortiz-de-Mandojana (2013)	Multiple and moderated regression analysis	88 green innovative firms and a matched-pairs sample of 70 pairs of green innovative and non–green innovative firms	1993-2013	EPO. GPI. CGD. ESI	ROA average from the 3 previous years	-

9.2 Appendix B – Examples of patents with the Y02 classification

CPC Code	Examples
Y02A	Adaption to climate change at coastal zones; at river basins Water conservation; efficient water supply; efficient water use Adaption or protecting infrastructure or their operation Adaption technologies in agriculture. forestry. livestock or agro alimentary production Adaption to climate change in human health protection Technologies having an indirect contribution to adaptation to climate change
Y02B	Integration of renewable energy sources in buildings Energy efficient lighting technologies Energy efficient heating. ventilation or air conditioning Technologies aiming at improving the efficiency of home appliances Energy efficient technologies in elevators. escalators and moving walkways
Y02B	Technologies for an efficient end-user side electric power management and consumption Architectural or constructional elements improving the thermal performance of buildings Enabling technologies or technologies with a potential or indirect contribution to greenhouse gas emissions mitigation
Y02C	CO_2 capture or storage Capture or disposal of greenhouse gases other than CO_2
Y02D	Energy efficient computing High level techniques for reducing energy consumption in communication networks Techniques for reducing energy consumption in wire-line communication networks Techniques for reducing energy consumption in wireless communication networks
Y02E	Energy generation through renewable energy sources Combustion technologies with mitigation potential Energy generation of nuclear origin Technologies for an efficient electrical power generation. transmission or distribution Technologies for the production of fuel of non-fossil origin Enabling technologies or technologies with a potential or indirect contribution to greenhouse gas emissions mitigation Other energy conversion or management systems reducing greenhouse gas emissions
Y02P	Climate change mitigation technologies related to metal processing Climate change mitigation technologies relating to chemical industry Climate change mitigation technologies relating to oil refining and petrochemical industry Climate change mitigation technologies relating to the processing of minerals Climate change mitigation technologies relating to agriculture. livestock or agro alimentary industries Climate change mitigation technologies in the production process for final industrial or consumer products Climate change mitigation technologies for sector wide applications Enabling technologies with a potential contribution to greenhouse gas emissions mitigation

CPC Code	Examples
Y02T	Climate change mitigation technologies related to road transport of goods or passengers Climate change mitigation technologies related to transportation of goods or passengers via railways Climate change mitigation technologies related to aeronautics or air transport Climate change mitigation technologies related to maritime or waterways transport
Y02W	Enabling technologies or technologies with a potential or indirect contribution to greenhouse gas emissions mitigation Climate change mitigation technologies for wastewater treatment Climate change mitigation technologies for solid waste management Enabling technologies or technologies with a potential or indirect contribution to greenhouse gas emissions mitigation

9.3 Appendix C – List of new European Green Patents granted in 2014

Owner	Publication Title	Number of citations
General Electric Company (US)	Waste heat recovery systems	6
The Boeing Company (US)	Self-configuring cabin management system	3
Siemens Aktiengesellschaft (DE)	Device for controlling energy transmission between transmission units in e.g. electric car, has detecting unit designed in such way that signal from reduced spatial region is detected, and control unit controlling energy transmission	7
Koninklijke Philips Electronics, N.V. (NL)	Methods and apparatus for controlling multiple light sources via single stabilising circuit to provide variable colour and/or colour temperature light	7
Honda Motor Company, Ltd. (JP)	Electric vehicle, such as scooter, is provided with batteries, where vehicle drive motor of electric vehicle is driven by electric energy from batteries, and battery frame is provided for supporting batteries	4
Johnson Matthey Public Limited Company (GB)	Exhaust system for a vehicular positive ignition internal combustion engine	6
General Motors Corporation (US)	Cooling blower system for motor vehicle with fuel cell propulsion has air branch-off wall to feed air from blower to conduit for fuel cell start-up	7
Volkswagen AG (DE)	Method for dosage of reducing agent carrier into exhaust passage of internal combustion engine for vehicle, involves determining temperature of reducing agent carrier based on empirically determined model	3
International Business Machines Corporation (US)	Solar cell and battery 3D integration	4

9.4 Appendix D – OLS results full sample

OLS REGRESSION ROA FULL SAMPLE 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-28.30	***	-11.54	***	4.38	***	-11.16	***	-32.21	***
	(-13.37)		(-6.95)		(5.34)		(-6.62)		(-14.77)	
Log(PAT)			-1.54	**	-1.02		-1.53	**	-3.73	***
			(-2.47)		(-1.59)		(-2.45)		(-6.18)	
Log(SIZE)	4.16	***							4.71	***
	(12.59)								(13.94)	
Log(AGE)	4.70	***	9.40	***			9.46	***	4.51	***
	(5.05)		(10.39)				(10.45)		(4.92)	
LEV	-0.11	***			-0.02		-0.04		-0.11	***
	(-4.10)				(-0.77)		(-1.33)		(-4.41)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	59.146	***	31.793	***	4.602	***	25.804	***	57.058	***
Adj. R2	18.1%		8.6%		1.1%		8.6%		20.4%	
Obs.	1314		1314		1314		1314		1314	

OLS REGRESSION ROA FULL SAMPLE 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-28.30	***	-9.82	***	5.81	***	-9.47	***	-29.44	***
	(-13.37)		(-5.65)		(6.27)		(-5.39)		(-12.77)	
Log(CIT)			0.19	*	0.27	**	0.19	*	-0.12	
			(1.89)		(2.57)		(1.85)		(-1.24)	
Log(SIZE)	4.16	***							4.27	***
	(12.59)								(12.50)	
Log(AGE)	4.70	***	9.09	***			9.16	***	4.67	***
	(5.05)		(10.04)				(10.09)		(5.02)	
LEV	-0.11	***			-0.02		-0.04		-0.11	***
	(-4.10)				(-0.74)		(-1.32)		(-4.20)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	59.146	***	31.101	***	5.643	***	25.242	***	49.567	***
Adj. R2	18.1%		8.4%		1.4%		8.5%		18.2%	
Obs.	1314		1314		1314		1314		1314	

OLS REGRESSION ROS FULL SAMPLE 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-67.19	***	-30.44	***	1.67		-30.83	***	-73.82	***
	(-18.02)		(-10.17)		(1.11)		(-10.15)		(-19.19)	
Log(PAT)			-1.81		-0.77		-1.83		-6.31	***
			(-1.61)		(-0.66)		(-1.63)		(-5.94)	
Log(SIZE)	8.68	***							9.61	***
	(14.91)								(16.13)	
Log(AGE)	9.99	***	19.85	***			19.79	***	9.68	***
	(6.10)		(12.17)				(12.12)		(5.98)	
LEV	-0.11	**			0.07		0.04		-0.12	***
	(-2.42)				(1.30)		(0.76)		(-2.68)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	80.813	***	39.444	***	2.573	**	31.659	***	74.986	***
Adj. R2	23.3%		10.5%		0.5%		10.5%		25.3%	
Obs.	1314		1314		1314		1314		1314	

OLS REGRESSION ROS FULL SAMPLE 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-67.19	***	-28.34	***	3.68	**	-28.71	***	-71.04	***
	(-18.02)		(-9.06)		(2.17)		(-9.07)		(-17.52)	
Log(CIT)			0.24		0.42	**	0.25		-0.42	**
			(1.31)		(2.18)		(1.33)		(-2.39)	
Log(SIZE)	8.68	***							9.05	***
	(14.91)								(15.06)	
Log(AGE)	9.99	***	19.48	***			19.41	***	9.89	***
	(6.10)		(11.94)				(11.88)		(6.05)	
LEV	-0.11	**			0.07		0.04		-0.12	***
	(-2.42)				(1.34)		(0.77)		(-2.61)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	80.813	***	39.198	***	3.661	***	31.466	***	68.536	***
Adj. R2	23.3%		10.4%		0.8%		10.4%		23.6%	
Obs.	1314		1314		1314		1314		1314	

OLS REGRESSION PROFIT MARGIN FULL SAMPLE 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-64.64	***	-29.13	***	1.56		-29.59	***	-71.01	***
	(-17.87)		(-10.05)		(1.08)		(-10.06)		(-19.03)	
Log(PAT)			-1.73		-0.74		-1.75		-6.08	***
			(-1.59)		(-0.65)		(-1.61)		(-5.99)	
Log(SIZE)	8.37	***							9.26	***
	(14.81)								(16.02)	
Log(AGE)	9.53	***	19.05	***			18.97	***	9.23	***
	(6.00)		(12.05)				(11.99)		(5.88)	
LEV	-0.10	**			0.07		0.04		-0.11	**
	(-2.22)				(1.45)		(0.92)		(-2.49)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	79.679	***	38.843	***	2.809	**	31.239	***	73.888	***
Adj. R2	23.1%		10.3%		0.5%		10.3%		25.0%	
Obs.	1314		1314		1314		1314		1314	

OLS REGRESSION PROFIT MARGIN FULL SAMPLE 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-64.64	***	-27.13	***	3.49	**	-27.56	***	-68.35	***
	(-17.87)		(-8.95)		(2.13)		(-8.98)		(-17.37)	
Log(PAT)			0.23		0.40	**	0.24		-0.40	**
			(1.29)		(2.16)		(1.32)		(-2.38)	
Log(SIZE)	8.37	***							8.72	***
	(14.81)								(14.96)	
Log(AGE)	9.53	***	(18.69)	***			18.61	***	9.44	***
	(6.00)		(11.82)				(11.75)		(5.95)	
LEV	-0.10	**			0.07		0.04		-0.11	**
	(-2.22)				(1.49)		(0.93)		(-2.42)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	79.679	***	38.602	***	3.877	***	31.050	***	67.578	***
Adj. R2	23.1%		10.3%		0.9%		10.3%		23.3%	
Obs.	1314		1314		1314		1314		1314	

9.5 Appendix E – Fixed Effects results full sample

FIXED EFFECTS MODEL ROA FULL SAMPLE 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-1.14	***	-1.18	***	-0.97	***	-0.48	***	-1.14	***
	(-7.61)		(-7.77)		(-7.03)		(-4.55)		(-7.61)	
Log(PAT)			-0.00		-0.00		-0.00		-0.00	
			(-0.16)		(-0.39)		(-0.07)		(-0.24)	
Log(SIZE)	0.13	***	0.15	***	0.16	***			(0.13)	***
	(6.09)		(6.47)		(7.64)				(6.09)	
Log(AGE)	0.18	***	0.15	**			0.32	***	0.18	***
	(2.86)		(2.28)				(5.35)		(2.84)	
LEV	-0.22	***			-0.21	***	-0.24	***	-0.22	***
	(-5.70)				(-5.44)		(-6.10)		(-5.71)	
Year Fixed Effects	Yes		Yes		Yes		Yes		Yes	
Firm Fixed Effects	Yes		Yes		Yes		Yes		Yes	
F-statistic	33.850	***	22.190	***	30.890	***	20.600	***	25.370	***
Obs.	1314		1314		1314		1314		1314	

FIXED EFFECTS MODEL ROA FULL SAMPLE 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-1.14	***	-1.18	***	-0.97	***	-0.48	***	-1.14	***
	(-7.61)		(-7.70)		(-6.98)		(-4.49)		(-7.56)	
Log(CIT)			0.00		0.00		0.00		-0.00	
			(0.18)		(0.26)		(0.00)		(-0.05)	
Log(SIZE)	0.13	***	0.14	***	0.16	***			(0.13)	***
	(6.09)		(6.46)		(7.61)				(6.09)	
Log(AGE)	0.18	***	0.15	**			0.32	***	0.18	***
	(2.86)		(2.26)				(5.32)		(2.84)	
LEV	-0.22	***			-0.21	***	-0.24	***	-0.22	***
	(-5.70)				(-5.42)		(-6.09)		(-5.69)	
Year Fixed Effects	Yes		Yes		Yes		Yes		Yes	
Firm Fixed Effects	Yes		Yes		Yes		Yes		Yes	
F-statistic	33.850	***	22.190	***	30.860	***	20.600	***	25.360	***
Obs.	1314		1314		1314		1314		1314	

FIXED EFFECTS MODEL ROS FULL SAMPLE 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-2.47	***	-2.52	***	-2.23	***	-0.97	***	-2.48	***
	(-9.67)		(-9.80)		(-9.38)		(-5.27)		(-9.67)	
Log(PAT)			0.01		0.01		0.02		0.01	
			(1.05)		(0.87)		(1.19)		(1.01)	
Log(SIZE)	0.31	***	0.32	***	0.34	***			0.31	***
	(8.19)		(8.41)		(9.75)				(8.16)	
Log(AGE)	0.27	**	0.24	**			0.61	***	0.28	**
	(2.49)		(2.23)				(5.74)		(2.54)	
LEV	-0.22	***			-0.20	***	-0.26	***	-0.22	***
	(-3.29)				(-3.05)		(-3.82)		(-3.28)	
Year Fixed Effects	Yes		Yes		Yes		Yes		Yes	
Firm Fixed Effects	Yes		Yes		Yes		Yes		Yes	
F-statistic	38.280	***	34.640	***	36.240	***	15.270	***	28.970	***
Obs.	1314		1314		1314		1314		1314	

FIXED EFFECTS MODEL ROS FULL SAMPLE 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-2.47	***	-2.52	***	-2.23	***	-0.97	***	-2.48	***
	(-9.67)		(-9.73)		(-9.36)		(-5.19)		(-9.62)	
Log(CIT)			-0.00		0.00		-0.00		-0.00	
			(-0.08)		(0.06)		(-0.13)		(-0.22)	
Log(SIZE)	0.31	***	0.32	***	0.34	***			0.31	***
	(8.19)		(8.44)		(9.73)				(8.19)	
Log(AGE)	0.27	**	0.24	**			0.60	***	0.27	**
	(2.49)		(2.17)				(5.66)		(2.49)	
LEV	-0.22	***			-0.20	***	-0.27	***	-0.22	***
	(-3.29)				(-3.06)		(-3.84)		(-3.30)	
Year Fixed Effects	Yes		Yes		Yes		Yes		Yes	
Firm Fixed Effects	Yes		Yes		Yes		Yes		Yes	
F-statistic	38.280	***	34.240	***	35.960	***	14.780	***	28.690	***
Obs.	1314		1314		1314		1314		1314	

FIXED EFFECTS MODEL PROFIT MARGIN FULL SAMPLE 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-2.37	***	-2.42	***	-2.11	***	-0.97	***	-2.38	***
	(-9.72)		(-9.85)		(-9.31)		(-5.52)		(-9.72)	
Log(PAT)			0.01		0.01		0.01		0.01	
			(1.05)		(0.85)		(1.19)		(1.01)	
Log(SIZE)	0.29	***	0.30	***	0.33	***			0.29	***
	(8.03)		(8.25)		(9.69)				(8.00)	
Log(AGE)	0.29	**	0.27	**			0.60	***	0.30	***
	(2.79)		(2.53)				(6.01)		(2.84)	
LEV	-0.22	***			-0.20	***	-0.26	***	-0.22	***
	(-3.36)				(-3.08)		(-3.88)		(-3.36)	
Year Fixed Effects	Yes		Yes		Yes		Yes		Yes	
Firm Fixed Effects	Yes		Yes		Yes		Yes		Yes	
F-statistic	38.570	***	34.770	***	35.920	***	16.390	***	29.180	***
Obs.	1314		1314		1314		1314		1314	

FIXED EFFECTS MODEL PROFIT MARGIN FULL SAMPLE 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-2.37	***	-2.42	***	-2.12	***	-0.97	***	-2.38	***
	(-9.72)		(-9.78)		(-9.28)		(-5.42)		(-9.67)	
Log(CIT)			0.00		0.00		-0.00		-0.00	
			(0.01)		(0.19)		(-0.05)		(-0.13)	
Log(SIZE)	0.29	***	0.30	***	0.33	***			0.29	***
	(8.03)		(8.28)		(9.67)				(8.03)	
Log(AGE)	0.29	**	0.26	**			0.60	***	0.30	***
	(2.79)		(2.46)				(5.91)		(2.79)	
LEV	-0.22	***			-0.20	***	-0.26	***	-0.21	***
	(-3.36)				(-3.09)		(-3.89)		(-3.36)	
Year Fixed Effects	Yes		Yes		Yes		Yes		Yes	
Firm Fixed Effects	Yes		Yes		Yes		Yes		Yes	
F-statistic	38.570	***	34.360	***	35.660	***	15.890	***	28.900	***
Obs.	1314		1314		1314		1314		1314	

9.6 Appendix F – Results split samples

DESCRIPTIVE STATISTICS < MEDIAN OF SIZE 2007 – 2014

Variables	N	Mean	Std. Dev.	Min	Max	Q1	Median	Q3
ROA (%)	657	2.49	20.52	-146.85	22.43	2.51	6.28	9.92
ROE (%)	657	3.83	32.31	-160.78	119.95	2.49	8.84	14.43
ROS (%)	657	-2.62	45.93	-260.37	35.06	2.85	7.36	11.73
Profit Margin (%)	657	-1.92	42.58	-246.55	33.16	2.85	7.36	11.52
Number of Patents	657	2.24	2.68	1	24	1	1	2
Number of Citations	657	1.49	3.77	0	26	0	0	0
Firm Size (× € 1,000,000)	657	2,088.94	1,911.76	0.28	6,473.00	379.36	1,530.20	3,358.30
Firm Age (years)	657	61.19	39.80	5	151	27	62	90.50
Firm Leverage (%)	657	13.15	11.24	0	48.38	2.90	11.63	20.58
Industry Control	657	0.38	0.48	0	1	0	0	1
Country Control	657	0.76	0.43	0	1	1	1	1

DESCRIPTIVE STATISTICS > MEDIAN OF SIZE 2007 – 2014

Variables	N	Mean	Std. Dev.	Min	Max	Q1	Median	Q3
ROA (%)	657	6.73	4.67	-5.46	21.34	3.69	6.12	9.20
ROE (%)	657	12.20	19.63	-71.53	119.56	5.80	11.08	17.45
ROS (%)	657	8.24	6.16	-5.79	32.12	4.48	7.26	10.84
Profit Margin (%)	657	8.19	6.13	-5.60	32.12	4.47	7.23	10.78
Number of Patents	657	9.48	17.81	1	166	1	3	9
Number of Citations	657	12.34	28.37	0	193	0	0	8.50
Firm Size (× € 1,000,000)	657	41,990.71	44,815.48	6,682.42	221,502.70	12,313.03	23,620.39	56,520.47
Firm Age (years)	657	80.02	37.08	9	167	59	82	105
Firm Leverage (%)	657	16.95	10.07	0.03	47.21	10.23	16.19	21.86
Industry Control	657	0.35	0.48	0	1	0	0	1
Country Control	657	0.83	0.37	0	1	1	1	1

CORRELATION MATRIX < MEDIAN OF SIZE 2007 – 2014

Variables	1	2	3	4	5	6	7	8	9
1. ROA	1	0.547**	0.744**	0.760**	-0.022	0.061	0.528**	0.380**	0.016
2. ROE		1	0.417**	0.431**	0.011	0.028	0.347**	0.243**	0.020
3. ROS			1	0.995**	-0.029	0.039	0.607**	0.394**	0.009
4. Profit Margin				1	-0.027	0.036	0.609**	0.392**	0.011
5. Log(PAT)					1	0.074	0.015	0.007	-0.092*
6. Log(CIT)						1	0.022	0.047	-0.109**
7. Log(SIZE)							1	0.528**	0.135**
8. Log(AGE)								1	0.058
9. Firm Leverage									1

CORRELATION MATRIX > MEDIAN OF SIZE 2007 – 2014

Variables	1	2	3	4	5	6	7	8	9
1. ROA	1	0.426**	0.791**	0.794**	-0.167**	0.008	-0.173**	-0.181**	-0.154**
2. ROE		1	0.360**	0.360**	-0.087*	0.102**	0.061	-0.064	-0.075
3. ROS			1	1.000**	-0.097*	-0.037	-0.019	-0.203**	0.065
4. Profit Margin				1	-0.099*	-0.034	-0.022	-0.204**	0.066
5. Log(PAT)					1	0.251**	0.325**	0.082*	-0.028
6. Log(CIT)						1	0.301**	0.012	-0.034
7. Log(SIZE)							1	0.020	0.169**
8. Log(AGE)								1	-0.032
9. Firm Leverage									1

OLS REGRESSION ROA < MEDIAN OF SIZE 2007 – 2014
Panel 1A

Model	1	2	3	4	5
Constant	-80.12 ***	-35.27 ***	-0.27	-35.17 ***	-80.43 ***
	(-15.66)	(-9.23)	(-0.14)	(-9.08)	(-15.69)
Log(PAT)		-1.91	-1.81	-1.95	-2.45
		(-0.71)	(-0.62)	(-0.72)	(-0.99)
Log(SIZE)	12.33 ***				12.34 ***
	(12.08)				(12.09)
Log(AGE)	7.98 ***	22.20 ***		22.23 ***	7.97 ***
	(3.49)	(10.27)		(10.25)	(3.48)
LEV	-0.10		0.04 **	-0.01	-0.10 *
	(-1.58)		(2.07)	(-0.17)	(-1.67)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	56.179 ***	27.774 ***	1.295	22.192 ***	46.980 ***
Adj. R2	29.6%	14.0%	0.2%	13.9%	29.6%
Obs.	657	657	657	657	657

OLS REGRESSION ROA < MEDIAN OF SIZE 2007 – 2014
Panel 1B

Model	1	2	3	4	5
Constant	-80.12 ***	-33.15 ***	2.23	-33.17 ***	-78.45
	(-15.66)	(-8.11)	(0.95)	(-8.06)	(-14.84)
Log(CIT)		0.31	0.48 *	0.31	0.28
		(1.26)	(1.81)	(1.26)	(1.25)
Log(SIZE)	12.33 ***				12.31
	(12.08)				(12.07)
Log(AGE)	7.98 ***	22.05 ***		22.04 ***	7.83
	(3.49)	(10.18)		(10.14)	(3.42)
LEV	-0.10		0.06	0.00	-0.09
	(-1.58)		(0.77)	(0.05)	(-1.42)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	56.179 ***	28.094 ***	2.020 *	22.442 ***	47.115 ***
Adj. R2	29.6%	14.2%	0.6%	14.0%	29.7%
Obs.	657	657	657	657	657

OLS REGRESSION ROA > MEDIAN OF SIZE 2007 – 2014
Panel 2A

Model	1		2		3		4		5	
Constant	24.56	***	12.37	***	7.71	***	13.96	***	22.12	***
	(7.34)		(10.45)		(14.86)		(11.63)		(6.17)	
Log(PAT)			-0.99	***	-1.22	***	-0.98	***	-0.69	*
			(-2.81)		(-3.48)		(-2.84)		(-1.87)	
Log(SIZE)	-1.41	***							-1.12	**
	(-3.22)								(-2.41)	
Log(AGE)	-3.74	***	-3.34	***			-3.56	***	-3.60	***
	(-6.09)		(-5.31)				(-5.75)		(-5.83)	
LEV	-0.08	***			-0.08	***	-0.09	***	-0.08	***
	(-4.65)				(-4.72)		(-5.12)		(-4.74)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	21.917	***	19.165	***	17.605	***	21.380	***	18.920	***
Adj. R2	13.8%		10.0%		9.2%		13.4%		14.1%	
Obs.	657		657		657		657		657	

OLS REGRESSION ROA > MEDIAN OF SIZE 2007 – 2014
Panel 2B

Model	1		2		3		4		5	
Constant	24.56	***	13.09	***	8.03	***	14.62	***	26.46	***
	(7.34)		(10.88)		(13.95)		(12.02)		(7.46)	
Log(CIT)			0.04		0.03		0.03		0.08	
			(0.83)		(0.61)		(0.61)		(1.61)	
Log(SIZE)	-1.41	***							-1.63	***
	(-3.22)								(-3.55)	
Log(AGE)	-3.74	***	-3.56	***			-3.77	***	-3.73	***
	(-6.09)		(-5.66)				(-6.10)		(-6.09)	
LEV	-0.08	***			-0.08	***	-0.09	***	-0.08	***
	(-4.65)				(-4.64)		(-5.17)		(-4.48)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	21.917	***	17.167	***	14.419	***	19.614	***	18.740	***
Adj. R2	13.8%		9.0%		7.6%		12.4%		14.0%	
Obs.	657		657		657		657		657	

OLS REGRESSION ROS < MEDIAN OF SIZE 2007 – 2014
Panel 1A

Model	1	2	3	4	5
Constant	-213.02 ***	-90.32 ***	-7.66 *	-89.67 ***	-213.88 ***
	(-19.92)	(-10.62)	(-1.72)	(-10.41)	(-19.97)
Log(PAT)		-5.32	-5.25	-5.58	-6.94
		(-0.88)	(-0.80)	(-0.92)	(-1.35)
Log(SIZE)	33.83 ***				33.88 ***
	(15.85)				(15.88)
Log(AGE)	13.13 ***	52.08 ***		52.24 ***	13.10 ***
	(2.74)	(10.82)		(10.83)	(2.74)
LEV	-0.31 **		0.04	-0.07	-0.32 **
	(-2.40)		(0.24)	(-0.49)	(-2.52)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	83.465 ***	30.177 ***	0.769	24.162 ***	69.946 ***
Adj. R2	38.6%	15.1%	0.0%	15.0%	38.7%
Obs.	657	657	657	657	657

OLS REGRESSION ROS < MEDIAN OF SIZE 2007 – 2014
Panel 1B

Model	1	2	3	4	5
Constant	-213.02 ***	-87.83 ***	-3.87	-87.49 ***	-211.86 ***
	(-19.92)	(-9.64)	(-0.74)	(-9.54)	(-19.15)
Log(CIT)		0.30	0.67	0.28	0.19
		(0.56)	(1.14)	(0.51)	(0.41)
Log(SIZE)	33.83 ***				33.82 ***
	(15.85)				(15.84)
Log(AGE)	13.13 ***	51.92 ***		52.05 ***	13.03 ***
	(2.74)	(10.77)		(10.76)	(2.72)
LEV	-0.31 **		0.07	-0.05	-0.30 **
	(-2.40)		(0.44)	(-0.34)	(-2.33)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	83.465 ***	30.038 ***	0.933	24.021 ***	69.493 ***
Adj. R2	38.6%	15.0%	0.0%	14.9%	38.5%
Obs.	657	657	657	657	657

OLS REGRESSION ROS > MEDIAN OF SIZE 2007 – 2014
Panel 2A

Model	1		2		3		4		5	
Constant	16.93	***	16.44	***	6.98	***	16.17	***	15.59	***
	(3.75)		(10.52)		(9.94)		(10.00)		(3.21)	
Log(PAT)			-0.35		-0.71		-0.36		-0.38	
			(-0.76)		(-1.49)		(-0.76)		(-0.76)	
Log(SIZE)	-0.08								0.08	
	(-0.14)								(0.13)	
Log(AGE)	-5.31	***	-5.27	***			-5.23	***	-5.23	***
	(-6.40)		(-6.33)				(-6.27)		(-6.26)	
LEV	0.02				0.03		0.02		0.02	
	(0.68)				(1.06)		(0.67)		(0.64)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	14.823	***	18.590	***	8.380	***	14.948	***	12.441	***
Adj. R2	9.5%		9.7%		4.3%		9.6%		9.5%	
Obs.	657		657		657		657		657	

OLS REGRESSION ROS > MEDIAN OF SIZE 2007 – 2014
Panel 2B

Model	1		2		3		4		5	
Constant	16.93	***	16.40	***	6.88	***	16.15	***	15.95	***
	(3.75)		(10.38)		(8.90)		(9.91)		(3.33)	
Log(CIT)			-0.04		-0.04		-0.04		-0.04	
			(-0.66)		(-0.60)		(-0.63)		(-0.62)	
Log(SIZE)	-0.08								0.03	
	(-0.14)								(0.05)	
Log(AGE)	-5.31	***	-5.34	***			-5.31	***	-5.31	***
	(-6.40)		(-6.46)				(-6.41)		(-6.40)	
LEV	0.02				0.02		0.02		0.01	
	(0.68)				(1.03)		(0.63)		(0.61)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	14.823	***	18.551	***	7.894	***	14.908	***	12.404	***
Adj. R2	9.5%		9.7%		4.0%		9.6%		9.4%	
Obs.	657		657		657		657		657	

OLS REGRESSION PROFIT MARGIN < MEDIAN OF SIZE 2007 – 2014
Panel 1A

Model	1	2	3	4	5
Constant	-197.39 ***	-83.19 ***	-7.11 *	-82.66 ***	-198.16 ***
	(-19.90)	(-10.54)	(-1.73)	(-10.34)	(-19.95)
Log(PAT)		-4.70	-4.61	-4.92	-6.18
		(-0.84)	(-0.76)	(-0.88)	(-1.30)
Log(SIZE)	31.46 ***				31.50 ***
	(15.90)				(15.93)
Log(AGE)	11.75 ***	47.99 ***		48.12 ***	11.73 ***
	(2.65)	(10.75)		(10.75)	(2.64)
LEV	-0.28 **		0.04	-0.06	-0.29 **
	(-2.35)		(0.29)	(-0.43)	(-2.46)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	83.380 ***	29.782 ***	0.789	23.833 ***	69.836 ***
Adj. R2	38.6%	14.9%	0.0%	14.8%	38.6%
Obs.	657	657	657	657	657

OLS REGRESSION PROFIT MARGIN < MEDIAN OF SIZE 2007 – 2014
Panel 1B

Model	1	2	3	4	5
Constant	-197.39 ***	-81.16 ***	-3.82	-80.88 ***	-196.55 ***
	(-19.90)	(-9.60)	(-0.78)	(-9.51)	(-19.16)
Log(CIT)		0.24	0.59	0.22	0.14
		(0.48)	(1.07)	(0.44)	(0.32)
Log(SIZE)	31.46 ***				31.45 ***
	(15.90)				(15.88)
Log(AGE)	11.75 ***	47.87 ***		47.97 ***	11.68 ***
	(2.65)	(10.70)		(10.68)	(2.63)
LEV	-0.28 **		0.07	-0.04	-0.27 **
	(-2.35)		(0.48)	(-0.30)	(-2.29)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	83.380 ***	29.640 ***	0.930	23.697 ***	69.405 ***
Adj. R2	38.6%	14.9%	0.0%	14.7%	38.5%
Obs.	657	657	657	657	657

OLS REGRESSION PROFIT MARGIN > MEDIAN OF SIZE 2007 – 2014
Panel 2A

Model	1		2		3		4		5	
Constant	17.22	***	16.37	***	6.91	***	16.09	***	15.88	***
	(3.83)		(10.53)		(9.89)		(10.00)		(3.29)	
Log(PAT)			-0.37		-0.72		-0.37		-0.38	
			(-0.80)		(-1.53)		(-0.80)		(-0.77)	
Log(SIZE)	-0.13								0.03	
	(-0.22)								(0.05)	
Log(AGE)	-5.30	***	-5.27	***			-5.23	***	-5.23	***
	(-6.43)		(-6.36)				(-6.29)		(-6.29)	
LEV	0.02				0.03		0.02		0.02	
	(0.71)				(1.08)		(0.69)		(0.67)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	14.978	***	18.782	***	8.485	***	15.109	***	12.572	***
Adj. R2	9.6%		9.8%		4.4%		9.7%		9.6%	
Obs.	657		657		657		657		657	

OLS REGRESSION PROFIT MARGIN > MEDIAN OF SIZE 2007 – 2014
Panel 2B

Model	1		2		3		4		5	
Constant	17.22	***	16.37	***	6.84	***	16.11	***	16.42	***
	(3.83)		(10.41)		(8.89)		(9.93)		(3.44)	
Log(CIT)			-0.04		-0.04		-0.04		-0.04	
			(-0.58)		(-0.52)		(-0.55)		(-0.51)	
Log(SIZE)	-0.13								-0.04	
	(-0.22)								(-0.07)	
Log(AGE)	-5.30	***	-5.34	***			-5.31	***	-5.31	***
	(-6.43)		(-6.50)				(-6.44)		(-6.43)	
LEV	0.02				0.03		0.02		0.02	
	(0.71)				(1.06)		(0.66)		(0.66)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	14.978	***	18.700	***	7.945	***	15.035	***	12.510	***
Adj. R2	9.6%		9.7%		4.1%		9.7%		9.5%	
Obs.	657		657		657		657		657	

9.7 Appendix G – Results 2-year lag

DESCRIPTIVE STATISTICS 2-YEAR LAG 2008 – 2014

Variables	N	Mean	Std. Dev.	Min	Max	Q1	Median	Q3
ROA (%)	1134	4.90	10.52	-55.86	21.83	3.19	6.08	9.44
ROE (%)	1134	7.26	28.10	-151.42	119.56	4.16	9.55	15.60
ROS (%)	1134	3.39	24.20	-131.89	32.80	3.75	7.11	10.98
Profit Margin (%)	1134	3.96	20.94	-107.01	32.80	3.73	7.05	10.82
Number of Patents	1134	5.65	12.67	1	166	1	2	4
Number of Citations	1134	7.13	20.72	0	184	0	0	4
Firm Size (× € 1,000,000)	1134	21,873.04	36,350.84	12.85	192,676.00	1,490.08	6,343.83	23,956.38
Firm Age (years)	1134	68.74	38.87	4	163	32	69	96
Firm Leverage (%)	1134	15.06	10.86	0	48.23	6.76	14.14	21.13
Industry Control	1134	0.37	0.48	0	1	0	0	1
Country Control	1134	0.79	0.41	0	1	1	1	1

CORRELATION MATRIX 2-YEAR LAG 2008 – 2014

Variables	1	2	3	4	5	6	7	8	9
1. ROA	1	0.578**	0.862**	0.886**	-0.058*	0.065*	0.391**	0.285**	-0.053
2. ROE		1	0.453**	0.478**	-0.004	0.058	0.284**	0.180**	-0.018
3. ROS			1	0.994**	-0.012	0.070*	0.470**	0.340**	0.036
4. Profit Margin				1	-0.016	0.067*	0.467**	0.339**	0.034
5. Log(PAT)					1	0.243**	0.269**	0.039	0.023
6. Log(CIT)						1	0.265**	0.056	-0.010
7. Log(SIZE)							1	0.388**	0.228**
8. Log(AGE)								1	0.071*
9. Firm Leverage									1

OLS REGRESSION ROA 2-YEAR LAG 2008 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-27.63	***	-9.43	***	4.60	***	-8.71	***	-31.31	***
	(-13.36)		(-6.08)		(5.51)		(-5.54)		(-14.64)	
Log(PAT)			-1.14	*	-0.70		-1.11	*	-3.48	***
			(-1.79)		(-1.06)		(-1.75)		(-5.73)	
Log(SIZE)	4.31	***							4.83	***
	(13.13)								(14.36)	
Log(AGE)	3.91	***	8.09	***			8.23	***	3.70	***
	(4.63)		(9.66)				(9.83)		(4.44)	
LEV	-0.14	***			-0.05	*	-0.07	**	-0.15	***
	(-5.44)				(-1.79)		(-2.51)		(-5.75)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	62.697	***	29.812	***	6.812	***	25.216	***	59.175	***
Adj. R2	21.2%		9.1%		2.0%		9.5%		23.3%	
Obs.	1134		1134		1134		1134		1134	

OLS REGRESSION ROA 2-YEAR LAG 2008 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-27.63	***	-7.85	***	5.97	***	-7.17	***	-28.65	***
	(-13.36)		(-4.84)		(6.38)		(-4.37)		(-12.70)	
Log(CIT)			0.19	**	0.24	***	0.19	**	-0.10	
			(2.19)		(2.65)		(2.14)		(-1.14)	
Log(SIZE)	4.31	***							4.41	***
	(13.13)								(12.98)	
Log(AGE)	3.91	***	7.88	***			8.02	***	3.87	***
	(4.63)		(9.42)				(9.58)		(4.58)	
LEV	-0.14	***			-0.05	*	-0.07	**	-0.14	***
	(-5.44)				(-1.78)		(-2.50)		(-5.52)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	62.697	***	30.245	***	8.319	***	25.555	***	52.477	***
Adj. R2	21.2%		9.2%		2.5%		9.7%		21.2%	
Obs.	1134		1134		1134		1134		1134	

OLS REGRESSION ROS 2-YEAR LAG 2008 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-85.50	***	-36.37	***	0.27		-36.67	***	-92.99	***
	(-18.53)		(-10.33)		(0.14)		(-10.23)		(-19.45)	
Log(PAT)			-1.17		-0.03		-1.18		-7.08	***
			(-0.81)		(-0.02)		(-0.82)		(-5.22)	
Log(SIZE)	10.97	***							12.04	***
	(14.99)								(16.01)	
Log(AGE)	11.99	***	22.91	***			22.85	***	11.56	***
	(6.37)		(12.04)				(11.98)		(6.21)	
LEV	-0.16	***			0.08		0.03		-0.17	***
	(-2.72)				(1.17)		(0.45)		(-2.96)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	81.011	***	37.813	***	1.739		30.270	***	73.592	***
Adj. R2	25.8%		11.4%		0.3%		11.3%		27.5%	
Obs.	1134		1134		1134		1134		1134	

OLS REGRESSION ROS 2-YEAR LAG 2008 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-85.50	***	-33.61	***	2.95		-33.90	***	-89.13	***
	(-18.53)		(-9.14)		(1.36)		(-9.09)		(-17.74)	
Log(CIT)			0.39	*	0.54	**	0.39	*	-0.34	*
			(1.94)		(2.54)		(1.95)		(-1.81)	
Log(SIZE)	10.97	***							11.33	***
	(14.99)								(14.97)	
Log(AGE)	11.99	***	22.58	***			22.52	***	11.85	***
	(6.37)		(11.89)				(11.82)		(6.29)	
LEV	-0.16	***			0.08		0.03		-0.17	***
	(-2.72)				(1.21)		(0.47)		(-2.85)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	81.011	***	38.690	***	3.367	***	30.976	***	68.193	***
Adj. R2	25.8%		11.6%		0.8%		11.5%		26.3%	
Obs.	1134		1134		1134		1134		1134	

OLS REGRESSION PROFIT MARGIN 2-YEAR LAG 2008 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-72.63	***	-30.23	***	1.22		-30.45	***	-79.18	***
	(-18.19)		(-9.92)		(0.73)		(-9.82)		(-19.13)	
Log(PAT)			-1.07		-0.09		-1.08		-6.18	***
			(-0.86)		(-0.07)		(-0.86)		(-5.26)	
Log(SIZE)	9.48	***							10.41	***
	(14.97)								(16.00)	
Log(AGE)	10.20	***	19.64	***			19.59	***	9.83	***
	(6.26)		(11.93)				(11.87)		(6.10)	
LEV	-0.14	***			0.06		0.02		-0.15	***
	(-2.77)				(1.11)		(0.40)		(-3.01)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	80.669	***	37.676	***	2.197	*	30.150	***	73.411	***
Adj. R2	25.8%		11.3%		0.4%		11.3%		27.5%	
Obs.	1134		1134		1134		1134		1134	

OLS REGRESSION PROFIT MARGIN 2-YEAR LAG 2008 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-72.63	***	-27.88	***	3.49	*	-28.11	***	-75.91	***
	(-18.19)		(-8.76)		(1.86)		(-8.71)		(-17.45)	
Log(PAT)			0.32	*	0.45	**	0.33	*	-0.31	*
			(1.87)		(2.47)		(1.88)		(-1.89)	
Log(SIZE)	9.48	***							9.80	***
	(14.97)								(14.96)	
Log(AGE)	10.20	***	19.35	***			19.31	***	10.07	***
	(6.26)		(11.77)				(11.71)		(6.18)	
LEV	-0.14	***			0.07		0.02		-0.15	***
	(-2.77)				(1.15)		(0.42)		(-2.91)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	80.669	***	38.457	***	3.739	***	30.779	***	67.967	***
Adj. R2	25.8%		11.5%		0.9%		11.5%		25.9%	
Obs.	1134		1134		1134		1134		1134	

9.8 Appendix H – Results patent-sensitive industries

DESCRIPTIVE STATISTICS PATENT-SENSITIVE INDUSTRIES 2007 – 2014

Variables	N	Mean	Std. Dev.	Min	Max	Q1	Median	Q3
ROA (%)	480	6.83	8.62	-42.83	22.21	4.29	7.44	10.49
ROE (%)	480	13.22	21.34	-74.90	119.95	6.05	11.02	18.85
ROS (%)	480	6.62	18.57	-113.99	28.54	5.05	8.77	12.93
Profit Margin (%)	480	6.68	18.10	-112.03	27.98	5.05	8.77	12.83
Number of Patents	480	7.16	18.17	1	166	1	2	4.75
Number of Citations	480	5.68	19.42	0	193	0	0	3
Firm Size (× € 1,000,000)	480	20,382.04	35,516.83	11.64	200,290.24	1,904.17	6,285.28	17,195.75
Firm Age (years)	480	78.53	39.45	7	164	51.25	78	103
Firm Leverage (%)	480	15.16	1039	0	47.21	7.89	14.53	21.56
Country Control	480	0.78	0.41	0	1	1	1	1

CORRELATION MATRIX PATENT-SENSITIVE INDUSTRIES 2007 – 2014

Variables	1	2	3	4	5	6	7	8	9
1. ROA	1	0.496**	0.849**	0.856**	-0.022	0.004	0.357**	0.181**	-0.071
2. ROE		1	0.437**	0.438**	0.107*	0.088	0.249**	0.042	0.069
3. ROS			1	0.997**	0.004	0.013	0.456**	0.317**	-0.007
4. Profit Margin				1	0.003	0.011	0.452**	0.314**	-0.009
5. Log(PAT)					1	0.274**	0.371**	0.156**	0.160**
6. Log(CIT)						1	0.265**	0.207**	0.064
7. Log(SIZE)							1	0.405**	0.284**
8. Log(AGE)								1	0.068
9. Firm Leverage									1

OLS REGRESSION ROA PATENT-SENSITIVE INDUSTRIES 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-18.25	***	-2.78		8.37	***	-2.05		-23.47	***
	(-5.97)		(-1.12)		(8.06)		(-0.81)		(-7.11)	
Log(PAT)			-0.93		-0.21		-0.75		-2.86	***
			(-1.23)		(-0.28)		(-0.98)		(-3.88)	
Log(SIZE)	3.89	***							4.48	***
	(8.26)								(9.17)	
Log(AGE)	1.34		5.94	***			5.99	***	1.44	
	(1.00)		(4.47)				(4.51)		(1.09)	
LEV	-0.15	***			-0.05		-0.06		-0.14	***
	(-4.05)				(-1.37)		(-1.51)		(-3.84)	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	23.664	***	7.282	***	1.227		6.044	***	22.505	***
Adj. R2	15.9%		3.8%		0.1%		4.0%		18.3%	
Obs.	480		480		480		480		480	

OLS REGRESSION ROA PATENT-SENSITIVE INDUSTRIES 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-18.25	***	-2.66		8.70	***	-1.96		-21.63	***
	(-5.97)		(-1.00)		(7.19)		(-0.73)		(-6.38)	
Log(CIT)			-0.07		0.04		-0.06		-0.26	**
			(-0.59)		(0.32)		(-0.52)		(-2.26)	
Log(SIZE)	3.89	***							4.10	***
	(8.26)								(8.58)	
Log(AGE)	1.34		5.83	***			5.92	***	1.63	
	(1.00)		(4.35)				(4.43)		(1.22)	
LEV	-0.15	***			-0.06		-0.06	*	-0.15	***
	(-4.05)				(-1.45)		(-1.66)		(-4.10)	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	23.664	***	6.874	***	1.234		5.861	***	20.111	***
Adj. R2	15.9%		3.5%		0.1%		3.9%		16.6%	
Obs.	480		480		480		480		480	

OLS REGRESSION ROS PATENT-SENSITIVE INDUSTRIES 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-68.27	***	-30.05	***	6.12	***	-29.63	***	-80.31	***
	(-10.91)		(-5.80)		(2.72)		(-5.61)		(-11.95)	
Log(PAT)			-1.70		0.23		-1.60		-6.60	***
			(-1.09)		(0.14)		(-1.01)		(-4.39)	
Log(SIZE)	9.24	***							10.60	***
	(9.58)								(10.65)	
Log(AGE)	9.54	***	20.52	***			20.54	***	9.77	***
	(3.47)		(7.39)				(7.40)		(3.62)	
LEV	-0.25	***			-0.02		-0.03		-0.23	***
	(-3.31)				(-0.22)		(-0.42)		(-3.07)	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	39.046	***	18.321	***	0.108		13.760	***	36.301	***
Adj. R2	24.1%		9.8%		0.0%		9.6%		26.9%	
Obs.	480		480		480		480		480	

OLS REGRESSION ROS PATENT-SENSITIVE INDUSTRIES 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-68.27	***	-31.35	***	6.40	**	-30.88	***	-78.19	***
	(-10.91)		(-5.77)		(2.45)		(-5.51)		(-11.32)	
Log(CIT)			-0.30		0.07		-0.29		-0.77	***
			(-1.17)		(0.25)		(-1.14)		(-3.25)	
Log(SIZE)	9.24	***							9.87	***
	(9.58)								(10.13)	
Log(AGE)	9.54	***	20.65	***			20.71	***	10.40	***
	(3.47)		(7.40)				(7.41)		(3.81)	
LEV	-0.25	***			-0.02		-0.04		-0.25	***
	(-3.31)				(-0.21)		(-0.53)		(-3.39)	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	39.046	***	18.389	***	0.123		13.842	***	33.981	***
Adj. R2	24.1%		9.8%		0.0%		9.7%		25.6%	
Obs.	480		480		480		480		480	

OLS REGRESSION PROFIT MARGIN PATENT-SENSITIVE INDUSTRIES 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-65.69	***	-28.83	***	6.12	***	-28.36	***	-77.35	***
	(-10.73)		(-5.70)		(2.80)		(-5.50)		(-11.76)	
Log(PAT)			-1.67		0.20		-1.56		-6.39	***
			(-1.09)		(0.13)		(-1.01)		(-4.35)	
Log(SIZE)	8.93	***							10.25	***
	(9.47)								(10.53)	
Log(AGE)	9.18	***	19.79	***			19.82	***	9.40	***
	(3.42)		(7.31)				(7.31)		(3.57)	
LEV	-0.24	***			-0.02		-0.04		-0.22	***
	(-3.34)				(-0.27)		(-0.47)		(-3.10)	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	38.114	***	17.924	***	0.142		13.477	***	35.432	***
Adj. R2	23.7%		9.6%		0.0%		9.4%		26.4%	
Obs.	480		480		480		480		480	

OLS REGRESSION PROFIT MARGIN PATENT-SENSITIVE INDUSTRIES 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-65.69	***	-30.19	***	6.32	**	-29.69	***	-75.46	***
	(-10.73)		(-5.59)		(2.48)		(-5.43)		(-11.18)	
Log(CIT)			-0.30		0.05		-0.29		-0.75	***
			(-1.21)		(0.19)		(-1.19)		(-3.28)	
Log(SIZE)	8.93	***							9.55	***
	(9.47)								(10.03)	
Log(AGE)	9.18	***	19.94	***			20.01	***	10.03	***
	(3.42)		(7.33)				(7.34)		(3.76)	
LEV	-0.24	***			-0.02		-0.05		-0.25	***
	(-3.34)				(-0.27)		(-0.59)		(-3.42)	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	38.114	***	18.027	***	0.149		13.587	***	33.264	***
Adj. R2	23.7%		9.6%		0.0%		9.5%		25.2%	
Obs.	480		480		480		480		480	

9.9 Appendix I – Results firms with at least one citation

DESCRIPTIVE STATISTICS >0 CITATIONS 2007 – 2014

Variables	N	Mean	Std. Dev.	Min	Max	Q1	Median	Q3
ROA (%)	435	6.28	6.67	-26.20	22.21	3.76	6.46	9.30
ROE (%)	435	11.56	23.36	-79.30	119.95	5.69	10.81	17.55
ROS (%)	435	6.43	14.48	-88.14	28.54	4.51	7.42	11.14
Profit Margin (%)	435	6.39	14.34	-88.14	27.98	4.47	7.42	11.11
Number of Patents	435	11.43	20.93	1	166	1	3	11
Number of Citations	435	20.89	32.17	1	193	4	8	22
Firm Size (× € 1,000,000)	435	37,151.25	47,372.40	22.88	200,290.24	3,133.00	16,610.39	57,334.00
Firm Age (years)	435	75.92	39.83	8	164	38	81	101
Firm Leverage (%)	435	14.73	10.35	0	45.10	7.06	13.70	20.79
Industry Control	435	0.32	0.47	0	1	0	0	1
Country Control	435	0.86	0.35	0	1	1	1	1

CORRELATION MATRIX >0 CITATIONS 2007 – 2014

Variables	1	2	3	4	5	6	7	8	9
1. ROA	1	0.450**	0.786**	0.786**	-0.174**	-0.094	0.158**	0.066	-0.171**
2. ROE		1	0.333**	0.337**	-0.018	-0.011	0.241**	0.029	-0.047
3. ROS			1	1.000**	-0.104*	-0.044	0.299**	0.126**	-0.042
4. Profit Margin				1	-0.105*	-0.045	0.304**	0.127**	-0.038
5. Log(PAT)					1	0.739**	0.348**	0.031	0.084
6. Log(CIT)						1	0.265**	0.035	0.046
7. Log(SIZE)							1	0.264**	0.317**
8. Log(AGE)								1	0.025
9. Firm Leverage									1

OLS REGRESSION ROA >0 CITATIONS 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-4.17		4.34	***	8.52	***	5.69	***	-9.60	***
	(-1.57)		(2.29)		(8.97)		(2.96)		(-3.49)	
Log(PAT)			-2.01	***	-1.75	***	-1.82	***	-3.26	***
			(-3.37)		(-2.96)		(-3.08)		(-5.52)	
Log(SIZE)	2.19	***							2.90	***
	(5.71)								(7.39)	
Log(AGE)	0.08		1.80	*			1.74	*	0.01	
	(0.08)		(1.73)				(1.69)		(0.01)	
LEV	-0.17	***			-0.10	***	-0.10	***	-0.17	***
	(-5.31)				(-3.31)		(-3.29)		(-5.57)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	11.570	***	5.527	***	7.612	***	6.687	***	15.380	***
Adj. R2	10.9%		4.0%		5.7%		6.1%		16.6%	
Obs.	435		435		435		435		435	

OLS REGRESSION ROA >0 CITATIONS 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-4.17		4.89	**	8.87	***	6.27	***	-6.68	**
	(-1.57)		(2.56)		(9.31)		(3.25)		(-2.44)	
Log(CIT)			-1.16	*	-1.00		-1.05		-2.10	***
			(-1.75)		(-1.53)		(-1.61)		(-3.24)	
Log(SIZE)	2.19	***							2.51	***
	(5.71)								(6.40)	
Log(AGE)	0.08		1.65				1.60		0.03	
	(0.08)		(1.57)				(1.54)		(0.03)	
LEV	-0.17	***			-0.11	***	-0.11	***	-0.17	***
	(-5.31)				(-3.51)		(-3.49)		(-5.48)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	11.570	***	3.407	***	5.930	***	5.236	***	11.604	***
Adj. R2	10.9%		2.2%		4.3%		4.7%		12.8%	
Obs.	435		435		435		435		435	

OLS REGRESSION ROS >0 CITATIONS 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-32.57	***	-3.71		7.63	***	-3.14		-43.59	***
	(-5.71)		(-0.89)		(3.60)		(-0.74)		(-7.35)	
Log(PAT)			-2.88	**	-2.53	*	-2.80	**	-6.61	***
			(-2.20)		(-1.91)		(-2.13)		(-5.18)	
Log(SIZE)	6.23	***							7.68	***
	(7.57)								(9.07)	
Log(AGE)	2.19		6.66	***			6.63	***	2.04	
	(0.99)		(2.92)				(2.90)		(0.95)	
LEV	-0.22	***			-0.05		-0.04		-0.22	***
	(-3.24)				(-0.68)		(-0.63)		(-3.40)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	13.717	***	3.566	***	1.529		2.928	**	16.599	***
Adj. R2	12.8%		2.3%		0.5%		2.2%		17.7%	
Obs.	435		435		435		435		435	

OLS REGRESSION ROS >0 CITATIONS 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-32.57	***	-2.79		8.24	***	-2.10		-37.55	***
	(-5.71)		(-0.67)		(3.89)		(-0.49)		(-6.37)	
Log(CIT)			-1.34		-1.09		-1.29		-4.15	***
			(-0.93)		(-0.75)		(-0.89)		(-2.98)	
Log(SIZE)	6.23	***							6.87	***
	(7.57)								(8.14)	
Log(AGE)	2.19		6.41	***			6.39	***	2.09	
	(0.99)		(2.80)				(2.79)		(0.95)	
LEV	-0.22	***			-0.06		-0.05		-0.22	***
	(-3.24)				(-0.82)		(-0.79)		(-3.37)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	13.717	***	2.548	**	0.748		2.162	*	13.118	***
Adj. R2	12.8%		1.4%		0.0%		1.3%		14.3%	
Obs.	435		435		435		435		435	

OLS REGRESSION PROFIT MARGIN >0 CITATIONS 2007 – 2014
Panel A

Model	1		2		3		4		5	
Constant	-32.73	***	-3.82		7.38	***	-3.33		-43.75	***
	(-5.80)		(-0.93)		(3.51)		(-0.79)		(-7.46)	
Log(PAT)			-2.87	**	-2.53	*	-2.80	**	-6.61	***
			(-2.22)		(-1.94)		(-2.15)		(-5.24)	
Log(SIZE)	6.23	***							7.68	***
	(7.64)								(9.16)	
Log(AGE)	2.16		6.62	***			6.59	***	2.01	
	(0.98)		(2.93)				(2.91)		(0.94)	
LEV	-0.21	***			-0.04		-0.04		-0.21	***
	(-3.18)				(-0.60)		(-0.55)		(-3.35)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	13.908	***	3.574	***	1.494		2.914	**	16.887	***
Adj. R2	12.9%		2.3%		0.5%		2.2%		18.0%	
Obs.	435		435		435		435		435	

OLS REGRESSION PROFIT MARGIN >0 CITATIONS 2007 – 2014
Panel B

Model	1		2		3		4		5	
Constant	-32.73	***	-2.91		7.99	***	-2.29		-37.73	***
	(-5.80)		(-0.70)		(3.81)		(-0.54)		(-6.47)	
Log(CIT)			-1.35		-1.11		-1.30		-4.16	***
			(-0.94)		(-0.77)		(-0.91)		(-3.02)	
Log(SIZE)	6.23	***							6.86	***
	(7.64)								(8.23)	
Log(AGE)	2.16		6.37	***			6.35	***	2.06	
	(0.98)		(2.81)				(2.80)		(0.95)	
LEV	-0.21	***			-0.05		-0.05		-0.22	***
	(-3.18)				(-0.74)		(-0.71)		(-3.31)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	13.908	***	2.545	**	0.699		2.134	*	13.329	***
Adj. R2	12.9%		1.4%		0.0%		1.3%		14.6%	
Obs.	435		435		435		435		435	

9.10 Appendix J – Results firm performance improvement

DESCRIPTIVE STATISTICS FIRM PERFORMANCE IMPROVEMENT AFTER 2 YEARS 2010 – 2014

Variables	N	Mean	Std. Dev.	Min	Max	Q1	Median	Q3
ROA (%)	811	14.90	126.52	-470.72	475.59	-26.92	-0.92	33.90
ROE (%)	811	18.14	223.65	-866.74	880.35	-35.74	-2.26	48.13
ROS (%)	811	19.64	136.10	-433.70	635.08	-21.24	2.82	36.89
Profit Margin (%)	811	16.93	125.23	-437.69	497.12	-20.75	3.11	36.89
Number of Patents	811	5.85	13.54	1	166	1	2	4
Number of Citations	811	7.41	10.77	0	184	0	0	5
Firm Size (× € 1,000,000)	811	23,147.03	38,385.36	14.43	190,331.17	1,665.99	6,478.54	25,313.31
Firm Age (years)	811	69.80	38.58	4	163	34	70	97
Firm Leverage (%)	811	15.16	10.85	0	49.20	6.83	14.43	21.54
Industry Control	811	0.38	0.49	0	1	0	0	1
Country Control	811	0.80	0.40	0	1	1	1	1

DESCRIPTIVE STATISTICS FIRM PERFORMANCE IMPROVEMENT AFTER 3 YEARS 2010 – 2014

Variables	N	Mean	Std. Dev.	Min	Max	Q1	Median	Q3
ROA (%)	811	28.32	131.77	-297.00	557.64	-27.89	0.91	45.24
ROE (%)	811	31.47	220.74	-756.82	879.65	-37.87	-0.60	64.36
ROS (%)	811	32.49	136.84	-317.75	620.77	-20.44	6.07	51.88
Profit Margin (%)	811	34.00	134.84	-246.87	639.83	-20.04	5.96	48.86
Number of Patents	811	5.85	13.54	1	166	1	2	4
Number of Citations	811	7.41	20.77	0	184	0	0	5
Firm Size (× € 1,000,000)	811	23,543.16	39,191.06	11.64	200,290.24	1,709.56	6,840.00	25,313.93
Firm Age (years)	811	70.80	38.58	5	164	35	71	98
Firm Leverage (%)	811	15.24	11.09	0	51.88	6.83	14.43	21.45
Industry Control	811	0.38	0.49	0	1	0	0	1
Country Control	811	0.80	0.40	0	1	1	1	1

CORRELATION MATRIX FIRM PERFORMANCE IMPROVEMENT AFTER 2 YEARS 2010 – 2014

Variables	1	2	3	4	5	6	7	8	9
1. ROA	1	0.560**	0.965**	0.971**	-0.006	-0.058	0.001	0.053	0.000
2. ROE		1	0.526**	0.547**	0.014	-0.071*	0.010	0.042	-0.019
3. ROS			1	0.986**	-0.017	-0.058	0.003	0.034	0.017
4. Profit Margin				1	-0.009	-0.053	0.020	0.040	0.020
5. Log(PAT)					1	0.243**	0.272**	0.044	0.013
6. Log(CIT)						1	0.278**	0.059	-0.027
7. Log(SIZE)							1	0.397**	0.201**
8. Log(AGE)								1	0.032
9. Firm Leverage									1

CORRELATION MATRIX FIRM PERFORMANCE IMPROVEMENT AFTER 3 YEARS 2010 – 2014

Variables	1	2	3	4	5	6	7	8	9
1. ROA	1	0.541**	0.969**	0.971**	-0.021	-0.064	-0.001	0.009	-0.051
2. ROE		1	0.535**	0.525**	0.038	-0.041	0.047	0.048	-0.062
3. ROS			1	0.993**	-0.020	-0.058	0.021	-0.002	-0.043
4. Profit Margin				1	-0.023	-0.059	0.009	-0.012	-0.039
5. Log(PAT)					1	0.243**	0.268**	0.046	-0.021
6. Log(CIT)						1	0.278**	0.061	-0.046
7. Log(SIZE)							1	0.399**	0.195**
8. Log(AGE)								1	0.023
9. Firm Leverage									1

OLS REGRESSION ROA IMPROVEMENT YEAR 2 2010 – 2014
Panel 1A

Model	1		2		3		4		5	
Constant	1.95		-1.94		15.66		-15.07		-1.93	
	(0.06)		(-0.05)		(0.45)		(-0.61)		(-0.05)	
Log(PAT)			-3.66		-4.42		-4.99		-3.62	
			(-0.37)		(-0.45)		(-0.53)		(-0.37)	
Log(SIZE)	-3.41		-2.75		1.17				-2.85	
	(-0.64)		(-0.51)		(0.23)				(-0.51)	
Log(AGE)	26.19	*	25.88	*			23.06	*	25.95	*
	(1.84)		(1.82)				(1.76)		(1.82)	
LEV	0.04				-0.01		-0.01		0.03	
	(0.10)				(-1.23)		(-0.03)		(0.08)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	1.003		1.029		0.368		0.978		0.857	
Adj. R2	0.0%		0.0%		0.0%		0.0%		0.0%	
Obs.	811		811		811		811		811	

OLS REGRESSION ROA IMPROVEMENT YEAR 2 2010 – 2014
Panel 1B

Model	1		2		3		4		5	
Constant	1.95		-23.42		-7.11		-27.24		-23.49	
	(0.06)		(-0.63)		(-0.20)		(-1.06)		(-0.63)	
Log(CIT)			-2.34	*	-2.47	*	-2.40	*	-2.35	*
			(-1.72)		(-1.81)		(-1.83)		(-1.72)	
Log(SIZE)	-3.41		-0.85		3.10				-0.78	
	(-0.64)		(-0.16)		(0.61)				(-0.14)	
Log(AGE)	26.19	*	24.98	*			24.13	*	24.93	*
	(1.84)		(1.76)				(1.85)		(1.75)	
LEV	0.04				-0.07		-0.04		-0.03	
	(0.10)				(-0.17)		(-0.09)		(-0.06)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	1.003		1.599		0.984		1.596		1.331	
Adj. R2	0.0%		0.4%		0.0%		0.4%		0.2%	
Obs.	811		811		811		811		811	

OLS REGRESSION ROA IMPROVEMENT YEAR 3 2010 – 2014
Panel 2A

Model	1	2	3	4	5
Constant	28.85	18.64	22.36	26.12	18.16
	(0.81)	(0.50)	(0.63)	(0.97)	(0.49)
Log(PAT)		-9.01	-10.40	-9.37	-10.23
		(-0.88)	(-1.02)	(-0.95)	(-1.00)
Log(SIZE)	0.19	-0.08	2.63		1.77
	(0.04)	(-0.01)	(0.50)		(0.31)
Log(AGE)	6.44	7.32		7.66	5.77
	(0.42)	(0.47)		(0.54)	(0.37)
LEV	-0.61		-0.66	-0.62	-0.65
	(-1.43)		(-1.53)	(-1.48)	(-1.51)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	0.823	0.568	0.996	1.005	0.852
Adj. R2	0.0%	0.0%	0.0%	0.0%	0.0%
Obs.	811	811	811	811	811

OLS REGRESSION ROA IMPROVEMENT YEAR 3 2010 – 2014
Panel 2B

Model	1	2	3	4	5
Constant	28.85	-2.56	-1.20	12.91	-4.51
	(0.81)	(-0.07)	(-0.03)	(0.47)	(-0.12)
Log(CIT)		-2.84 **	-3.13 **	-2.85 **	-3.10 **
		(-2.00)	(-2.20)	(-2.09)	(-2.18)
Log(SIZE)	0.19	1.57	4.38		3.68
	(0.04)	(0.28)	(0.83)		(0.64)
Log(AGE)	6.44	6.45		8.64	4.68
	(0.42)	(0.42)		(0.61)	(0.30)
LEV	-0.61		-0.72 *	-0.65	-0.71 *
	(-1.43)		(-1.70)	(-1.57)	(-1.67)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	0.823	1.221	1.763	1.699	1.483
Adj. R2	0.0%	0.1%	0.5%	0.4%	0.4%
Obs.	811	811	811	811	811

OLS REGRESSION ROS IMPROVEMENT YEAR 2 2010 – 2014
Panel 1A

Model	1	2	3	4	5
Constant	9.19	1.53	13.89	-5.92	1.63
	(0.25)	(0.04)	(0.37)	(-0.22)	(0.04)
Log(PAT)		-7.31	-7.60	-7.83	-7.05
		(-0.69)	(-0.72)	(-0.77)	(-0.67)
Log(SIZE)	-2.73	-0.97	1.16		-1.64
	(-0.47)	(-0.17)	(0.21)		(-0.27)
Log(AGE)	18.55	17.62		16.43	18.09
	(1.21)	(1.15)		(1.16)	(1.18)
LEV	0.26		0.21	0.22	0.24
	(0.56)		(0.47)	(-1.26)	(0.53)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	0.543	0.575	0.355	0.617	0.526
Adj. R2	0.0%	0.0%	0.0%	0.0%	0.0%
Obs.	811	811	811	811	811

OLS REGRESSION ROS IMPROVEMENT YEAR 2 2010 – 2014
Panel 1B

Model	1	2	3	4	5
Constant	9.19	-18.67	-6.91	-17.71	-18.21
	(0.25)	(-0.47)	(-0.18)	(-0.64)	(-0.45)
Log(CIT)		-2.58 *	-2.61 *	-2.52 *	-2.53 *
		(-1.77)	(-1.78)	(-1.79)	(-1.72)
Log(SIZE)	-2.73	0.64	2.77		0.10
	(-0.47)	(0.11)	(0.50)		(0.02
Log(AGE)	18.55	16.82		17.30	17.19
	(1.21)	(1.10)		(1.23)	(1.12)
LEV	0.26		0.15	0.19	0.18
	(0.56)		(0.34)	(0.42)	(0.41)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	0.543	1.105	0.886	1.138	0.947
Adj. R2	0.0%	0.1%	0.0%	0.1%	0.0%
Obs.	811	811	811	811	811

OLS REGRESSION ROS IMPROVEMENT YEAR 3 2010 – 2014
Panel 2A

Model	1	2	3	4	5
Constant	18.70	6.22	2.84	35.02	5.74
	(0.50)	(0.16)	(0.08)	(1.26)	(0.15)
Log(PAT)		-11.18	-12.29	-9.26	-12.40
		(-1.06)	(-1.16)	(-0.91)	(-1.17)
Log(SIZE)	4.59	4.65	5.90		6.49
	(0.80)	(0.79)	(1.08)		(1.08)
Log(AGE)	-3.15	-2.41		3.00	-3.97
	(-0.20)	(-0.15)		(0.20)	(-0.25)
LEV	-0.61		-0.64	-0.54	-0.65
	(-1.37)		(-1.44)	(-1.25)	(-1.45)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	0.830	0.680	1.092	0.867	0.919
Adj. R2	0.0%	0.0%	0.1%	0.0%	0.0%
Obs.	811	811	811	811	811

OLS REGRESSION ROS IMPROVEMENT YEAR 3 2010 – 2014
Panel 2B

Model	1	2	3	4	5
Constant	18.70	-14.29	-19.76	22.74	-16.23
	(0.50)	(-0.35)	(-0.51)	(0.79)	(-0.40)
Log(CIT)		-2.99 **	-3.23 **	-2.69 *	-3.25 **
		(-2.03)	(-2.19)	(-1.89)	(-2.20)
Log(SIZE)	4.59	6.13	7.49		8.24
	(0.80)	(1.05)	(1.37)		(1.38)
Log(AGE)	-3.15	-3.22		3.88	-4.99
	(-0.20)	(-0.20)		(0.26)	(-0.31)
LEV	-0.61		-0.70	-0.58	-0.71
	(-1.37)		(-1.59)	(-1.33)	(-1.60)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	0.830	1.287	1.786	1.422	1.502
Adj. R2	0.0%	0.2%	0.5%	0.3%	0.4%
Obs.	811	811	811	811	811

OLS REGRESSION PROFIT MARGIN IMPROVEMENT YEAR 2 2010 – 2014
Panel 1A

Model	1	2	3	4	5
Constant	-6.63	-13.20	-1.78	-8.77	-13.10
	(-0.20)	(-0.37)	(-0.05)	(-0.36)	(-0.37)
Log(PAT)		-6.27	-6.55	-5.59	-6.04
		(-0.65)	(-0.67)	(-0.60)	(-0.62)
Log(SIZE)	0.00	1.52	3.52		0.94
	(0.00)	(0.28)	(0.70)		(0.17)
Log(AGE)	17.10	16.29		17.66	16.71
	(1.21)	(1.15)		(1.36)	(1.18)
LEV	0.22		0.18	0.23	0.21
	(0.54)		(0.44)	(0.56)	(0.51)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	0.728	0.753	0.526	0.800	0.671
Adj. R2	0.0%	0.0%	0.0%	0.0%	0.0%
Obs.	811	811	811	811	811

OLS REGRESSION PROFIT MARGIN IMPROVEMENT YEAR 2 2010 – 2014
Panel 1B

Model	1		2		3		4		5	
Constant	-6.63		-32.19		-21.37		-19.23		-31.79	
	(-0.20)		(-0.87)		(-0.60)		(-0.75)		(-0.86)	
Log(CIT)			-2.37	*	-2.40	*	-2.15	*	-2.32	*
			(-1.76)		(-1.78)		(-1.65)		(-1.72)	
Log(SIZE)	0.00		3.06		5.07				2.60	
	(0.00)		(0.57)		(1.00)				(0.47)	
Log(AGE)	17.10		15.53				18.51		15.86	
	(1.21)		(1.10)				(1.43)		(1.12)	
LEV	0.22				0.13		0.20		0.16	
	(0.54)				(0.32)		(0.50)		(0.38)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	0.728		1.293		1.069		1.277		1.101	
Adj. R2	0.0%		0.2%		0.0%		0.2%		0.1%	
Obs.	811		811		811		811		811	

OLS REGRESSION PROFIT MARGIN IMPROVEMENT YEAR 3 2010 – 2014
Panel 2A

Model	1	2	3	4	5
Constant	34.55	22.33	17.42	43.78	21.92
	(0.94)	(0.58)	(0.48)	(1.59)	(0.57)
Log(PAT)		-11.04	-11.91	-9.74	-12.08
		(-1.06)	(-1.14)	(-0.97)	(-1.15)
Log(SIZE)	2.99	3.27	3.93		4.85
	(0.53)	(0.57)	(0.73)		(0.82)
Log(AGE)	-5.37	-4.83		-0.97	-6.17
	(-0.34)	(-0.31)		(-0.07)	(-0.39)
LEV	-0.51		-0.54	-0.48	-0.55
	(-1.17)		(-1.24)	(-1.11)	(-1.26)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	0.674	0.622	0.911	0.806	0.784
Adj. R2	0.0%	0.0%	0.0%	0.0%	0.0%
Obs.	811	811	811	811	811

OLS REGRESSION PROFIT MARGIN IMPROVEMENT YEAR 3 2010 – 2014
Panel 2B

Model	1	2	3	4	5
Constant	34.55	3.12	-3.60	31.96	1.44
	(0.94)	(0.08)	(-0.09)	(1.13)	(0.04)
Log(CIT)		-2.86 **	-3.05	-2.64 *	-3.08 **
		(-1.97)	(-2.10)	(-1.89)	(-2.12)
Log(SIZE)	2.99	4.63	5.38		6.45
	(0.53)	(0.80)	(1.00)		(1.09)
Log(AGE)	-5.37	-5.59		-0.17	-7.12
	(-0.34)	(-0.35)		(-0.01)	(-0.45)
LEV	-0.51		-0.60	-0.51	-0.62
	(-1.17)		(-1.38)	(-1.19)	(-1.40)
Industry Control	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes
F-statistic	0.674	1.177	1.533	1.333	1.310
Adj. R2	0.0%	0.1%	0.3%	0.2%	0.2%
Obs.	811	811	811	811	811

9.11 Appendix K – Results citation dummy

CORRELATION MATRIX DUMMY CITATION 2007 – 2014

Variables	1	2	3	4	5	6	7	8	9
1. ROA	1	0.512**	0.858**	0.865**	-0.064*	0.066*	0.375**	0.280**	-0.022
2. ROE		1	0.441**	0.447**	-0.006	0.079**	0.263**	0.160**	-0.005
3. ROS			1	0.997**	-0.031	0.056*	0.448**	0.323**	0.037
4. Profit Margin				1	-0.031	0.055*	0.446**	0.321**	0.042
5. Log(PAT)					1	0.206**	0.261**	0.051	0.022
6. Citation Dummy						1	0.252**	0.076**	-0.020
7. Log(SIZE)							1	0.403**	0.227**
8. Log(AGE)								1	0.060*
9. Firm Leverage									1

OLS REGRESSION ROA CITATION DUMMY 2007 – 2014

Model	1		2		3		4		5	
Constant	-28.30	***	-10.99	***	4.15	***	-10.62	***	-28.58	***
	(-13.37)		(-6.69)		(5.03)		(-6.38)		(-13.37)	
Citation Dummy			1.28	**	1.75	***	1.25	**	-0.57	
			(2.05)		(2.71)		(2.00)		(-0.94)	
Log(SIZE)	4.16	***							4.24	***
	(12.59)								(12.44)	
Log(AGE)	4.70	***	9.09	***			9.15	***	4.68	***
	(5.05)		(10.03)				(10.09)		(5.03)	
LEV	-0.11	***			-0.02		-0.04		-0.11	***
	(-4.10)				(-0.73)		(-1.31)		(-4.17)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	59.146	***	31.266	***	5.818	***	25.368	***	49.432	***
Adj. R2	18.1%		8.4%		1.4%		8.5%		18.1%	
Obs.	1314		1314		1314		1314		1314	

OLS REGRESSION ROS CITATION DUMMY 2007 – 2014

Model	1		2		3		4		5	
Constant	-67.19	***	-29.80	***	1.14		-30.19	***	-68.32	***
	(-18.02)		(-10.08)		(0.76)		(-10.06)		(-18.17)	
Citation Dummy			1.54		2.62	**	1.56		-2.32	**
			(1.36)		(2.21)		(1.39)		(-2.16)	
Log(SIZE)	8.68	***							9.00	***
	(14.91)								(15.01)	
Log(AGE)	9.99	***	19.48	***			19.41	***	9.91	***
	(6.10)		(11.94)				(11.88)		(6.06)	
LEV	-0.11	**			0.07		0.04		-0.12	***
	(-2.42)				(1.35)		(0.77)		(-2.59)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	80.813	***	39.236	***	3.700	***	31.498	***	68.308	***
Adj. R2	23.3%		10.4%		0.8%		10.4%		23.5%	
Obs.	1314		1314		1314		1314		1314	

OLS REGRESSION PROFIT MARGIN CITATION DUMMY 2007 – 2014

Model	1		2		3		4		5	
Constant	-64.64	***	-28.52	***	1.06		-28.98	***	-65.73	***
	(-17.87)		(-9.95)		(0.72)		(-9.97)		(-18.02)	
Citation Dummy			1.46		2.50	**	1.49		-2.25	**
			(1.34)		(2.19)		(1.37)		(-2.16)	
Log(SIZE)	8.37	***							8.67	***
	(14.81)								(14.92)	
Log(AGE)	9.53	***	18.69	***			18.61	***	9.46	***
	(6.00)		(11.82)				(11.75)		(5.96)	
LEV	-0.10	**			0.07		0.04		-0.11	***
	(-2.22)				(1.50)		(0.93)		(-2.40)	
Industry Control	Yes		Yes		Yes		Yes		Yes	
Country Control	Yes		Yes		Yes		Yes		Yes	
F-statistic	79.679	***	38.635	***	3.909	***	31.078	***	67.360	***
Adj. R2	23.1%		10.3%		0.9%		10.3%		23.3%	
Obs.	1314		1314		1314		1314		1314	