Norwegian School of Economics
Bergen, Fall 2022

Uncovering the Value of Green Innovation in the Context of Cost of Equity

An Empirical Study of how Green Innovation Efforts Impact the Cost of Equity

Leon Langvik Flåten & Eirik Midtun Seppola

Supervisor: Maximilian Rohrer

Master thesis, Economics and Business Administration

Major: Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgements

This thesis is written as part of our Master of Science in Financial Economics at the Norwegian School of Economics. We are humble and grateful for our academic development and accomplishments during our time in Bergen.

We want to express our gratitude to our supervisor, Maximilian Rohrer, for providing us with guidance and feedback throughout the writing process. Additionally, we would like to thank our fellow students for valuable discussions during the master's degree.

Through the thesis, we have acquired valuable knowledge within econometric analysis and theoretical research. In addition, we have gained further knowledge within our interest of sustainable finance, particularly the link to green innovation. Our data processing also required skills in Python and R, where we have developed and improved our skills considerably.

Norwegian School of Economics

Bergen, December 2022

Leon Langvik Flåten

Eirik Midtun Seppola

Abstract

This thesis investigates the relationship between green innovation and the cost of equity for the 500 largest European public firms from 2000 to 2019. The findings show that more green innovation is associated with a lower cost of equity, although the effect is small. The results are robust to alternative measures of green innovation but sensitive to the definition of cost of equity. We use a 2SLS regression with initial green innovation as an instrument to address endogeneity, and the results remain robust. Previous literature discuss two main mechanisms (increased investor base and lower risk), but we find weak support. In conclusion, green innovation can reduce the cost of equity, but further research is needed to understand the mechanisms behind the relationship.

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1 Introduction

One of the world's biggest challenges is to stay within the limits of acceptable global warming. However, the world needs to balance economic growth and sustainable development. In this context, there is an ongoing discussion about which role the financial market should play. Stock markets are a useful tool for promoting social and economic development (Levine & Zervos, 1996) and could be a key contributor to the climate transition. In recent years, financial markets have started incorporating climate change opportunities and risks into their investment decisions (OECD, 2021).

IEA (2021a) considers innovation as a key feature in reaching net zero and states that most of the technology required to reach the emission reduction target of 2030 is available today. However, most of the technology to reach the goal of net zero emission after 2030 is still under development or at the prototype stage. This means that "major innovation efforts are vital in this decade so that the technologies necessary for net-zero emissions reach markets as soon as possible" (IEA, 2021a, p. 184).

This thesis aims to find out how green innovation affects the cost of equity. By studying the cost of equity, we can better understand the factors influencing financial performance and identify strategies to improve it. ESG and CSR scores have been seen as good indicators of a firm's social and environmental responsibility and previous studies have found that a high ESG/CSR score results in a lower cost of equity (e.g. (El Ghoul et al., 2011)). The thesis is inspired by El Ghoul et al. (2011) and will follow a similar structure. In contrast, we will investigate the relationship between green innovation and cost of equity. Green innovation is interesting because it is seen as a key driver in fighting climate change (IEA, 2021a). Moreover, it is also interesting to see whether financial markets react positively to companies with sustainable development activities. Overall, examining the relationship between green innovation and the cost of equity can provide valuable insights into the financial implications of investing in green technology.

The thesis builds on the findings from Elmawazini et al. (2022). They find, by looking at U.S. public firms, that greater green technology innovation is associated with a lower cost of equity. Based on previous literature, we hypothesize that firms that engage in green innovation will get a lower cost of equity because they can 1) attract a larger investor base and 2) lower their perceived risk. To test the hypothesis, we will make use of the OECD's large patent database to analyze the relationship between green innovation and the cost of equity. The analysis follows prior research and applies a fixed effect model with several control variables, and year- and industry-fixed effects.

To further validate our results, we use different measures of green innovation and a alternative calculation of the cost of equity. There is no universal rule for measuring innovation and cost of equity, and we want to ensure the models' are not subject to biases. To ensure that our findings are robust to endogeneity concerns, we use a 2SLS regression where we follow prior research and use the firms initial value of green innovation as an instrument variable. Furthermore, to better understand the results, we run a mechanism test. This test investigates how green innovation impacts the two channels of arguments, 1) the investor base channel and 2) the risk channel.

The findings in our main analysis are consistent with previous research like El Ghoul et al. (2011) and Elmawazini et al. (2022). Similar to Elmawazini et al. (2022), we find a small effect. Our findings suggest that a 20% increase in our green innovation measure is associated with a 0.01 percentage-point reduction in the cost of equity. Our results are robust when using different measures of innovation. The results also remain robust when using the 2SLS regression with the firms initial value of green innovation as instrument variable. However, the results are not robust to using the alternative measure of the cost of equity. Finally, the mechanism test did not provide a clear picture but could indicate that green innovation may attract more investors and reduce the firm's risk.

These findings contribute to the literature combining finance and sustainable development. We add to the existing literature examining how sustainable practices affect the cost of equity. Prior research focuses on the link between ESG/CSR and the cost of equity. However, this work contributes to early research into an understudied part of the literature on sustainable finance. The focus on green innovation offers a more targeted approach to investigating the relationship between sustainable practices and the cost of equity. In addition, the thesis can provide insight into the potential financial benefits of green innovation. Therefore, it could help companies and investors decide how to allocate their capital for long-term financial success. Additionally, this thesis contributes to the findings of Elmawazini et al. (2022), by investigating the mechanisms behind the relationship.

The structure of the thesis is as follows. In Chapter 2 we discuss theory and relevant literature to our research question. Then Chapter 3 presents our hypothesis based on the findings from the literature review. Furthermore, Chapter 4 describes the data preparation for the quantitative analysis. We describe our data sources and the process of gathering and tidying the data. Chapter 5 explains the research method used; it covers the selection of variables and the regression models. Chapter 6 presents the empirical results, including descriptive statistics, our main regression table, and the robustness tests. Chapter 7 investigate and discuss the mechanisms behind our results. Chapter 7 also discusses potential endogeneity concerns. Finally, Chapter 8 concludes the work, and Chapter 9 presents limitations and suggestions for further research.

2 Literature Review

Several researchers have studied the cost of equity, and there is a vast amount of available literature. However, there are few studies about the link between green innovation and the cost of equity. In fact, to the best of our knowledge, there is only one article that looks at the same relationship: the article from Elmawazini et al. from August 2022 (Elmawazini et al., 2022). Their findings show, by looking at U.S. public firms, that greater green technology innovation could be associated with a lower cost of equity capital (Elmawazini et al., 2022). In contrast to Elmawazini et al. this thesis looks at European companies.

This chapter presents relevant theory and previous literature. First, we need to clarify how to measure green innovation. Second, to examine how a firm's cost of equity is affected by green innovation, we need to understand the cost of equity theory and through which channels green innovation can affect it. Third, we find relevant literature to the channels discussed in the second section of this chapter. Finally, in the next chapter we present a hypothesis based on the literature discussed in this chapter.

2.1 Measuring Green Innovation

Green innovation can be defined as the process that leads to the creation of new technologies to reduce environmental impact, such as pollution and negative consequences of resource extraction (Castellacci & Lie, 2017). OECD divides green innovation into two primary measures: 1) Green Research & Development (R&D) and: 2) Green Patents (OECD, 2017). Green R&D is defined as R&D addressing environmental problems (OECD, 2007), while green patents are defined as patents providing an environmental benefit (Innovation Norway, 2022). It is important to note that although R&D and patenting are the two main measures of innovation, R&D is often the input measure, and patent is the output measure. The simplified process of green innovation can be divided into four components, as seen in Figure 2.1 (Grazzi et al., 2019).

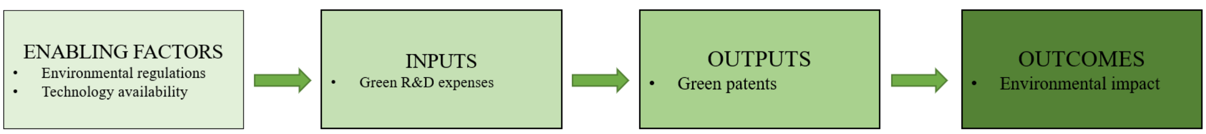

Figure 2.1: Green Innovation Process

Patents are the most used green innovation measure, and patents are advantageous compared to R&D (Kemp, 2009). High R&D spending does not guarantee successful innovation, and the success of green innovation efforts should be measured based on the output rather than the input. Ideally, both measures should be used to quantify the effect of green innovation. However, patent data are available and quantitative, while obtaining data for green R&D expenses at the firm level is challenging due to a lack of data.

Consistent with former studies on green innovation, we use green patents as a proxy for green innovation (Berrone et al., 2015; Brunnermeier & Cohen, 2003). Green patents can be a credible indicator of a firm's environmental commitments because innovators face substantial expenses to develop green technologies (Berrone et al., 2015). Furthermore, Trajtenberg (1990) concluded that citations is the best indicator for measuring green innovation. He argued that citations are the better indicator as there is such a big difference in how effective the patent is both technologically and economically (Trajtenberg, 1990). Additionally, other studies find that there is a strong correlation between the number of citations and the market value of the patent (Hall et al., 2005; Harhoff et al., 2005). Finally, green innovation is essential for firms as it can improve revenue growth, their competitive advantage (Buddelmeyer et al., 2006), and access to capital markets (Hegde et al., 2021).

2.2 Cost of Equity

The cost of equity can be defined as the rate of return equity holders demand investing in an asset. It is the compensation the shareholder demand in exchange for the risk of investing. Ultimately, the cost of equity is an important factor in a company's ability to raise capital and attract and retain investors.

The Capital Asset Pricing Model (CAPM) is the most used model to estimate the cost of equity. The model was introduced in the 1960s by famous economists such as Jack Treynor (1961) and William Sharpe (1964). The CAPM model is based on the relationship between the stock's volatility and the risk of the market, as shown in the equation below:

$$COE = r_f + \beta \times (R_m - r_f) \tag{2.1}$$

Where:

COE = Cost of Equity
r_f = Risk-free rate
β = Asset risk compared to market
R_m = Market rate of return

The cost of equity is complex and influenced by various factors. The main factors affecting the cost of equity are financial performance, market risk, and competition in the industry. In the case of green innovation, the level of risk and future return can play a significant role. Additionally, investors' sentiments and expectations about future growth and profitability can play a role in determining the cost of equity. Overall, based on previous literature (e.g. (Breuer et al., 2018; El Ghoul et al., 2011; Elmawazini et al., 2022)), we have identified two different channels where green innovation could affect the cost of equity.

1) Investor Base Channel:
Green innovation can help a firm reduce its environmental impact, thereby enhancing its reputation and making the company more attractive to investors, especially responsible investors. This could increase the investor base and demand for the stock and thus reduce the cost of equity.

2) Risk Channel:
The investment becomes less risky when a company improves its reputation and financial stability. Moreover, the cost of equity can be affected by the potential risks and uncertainties associated with the transition to a more sustainable economy. As a result, investors could be hesitant to invest in companies exposed to transition risk. For example, green innovation can reduce a company's risk profile by lowering the potential negative impacts of environmental regulations.

2.3 Investor Base Channel

As mentioned in Section 2.2, we identified that green innovation can affect the cost of equity through responsible investors. In this section, we will discuss how responsible investors could affect the cost of equity.

In recent years, Socially Responsible Investors (SRI) have grown in popularity among private investors and large fund managers. This investment strategy involves investing in companies that offer a financial return while providing environmental benefits. In recent years, there has been increased focus on investments in environmentally friendly companies, which have often been called "sustainable investing". Norges Bank Investment Management (NBIM) has also started to prioritize sustainable investing. They have increased investment in companies that have positioned themselves to take advantage of the economic opportunities of the energy transition (NBIM, 2021a).

Figure 2.2 shows how much the investments in sustainable funds in Europe have increased during the last ten years. The pillars in the figure describe the value of assets under management (AUM) allocated to sustainable funds. From 2016 to 2020 the number of sustainable funds have almost doubled, and the AUM have more than quadrupled from $302 billion to over $1.3 trillion (UNCTAD, 2021).

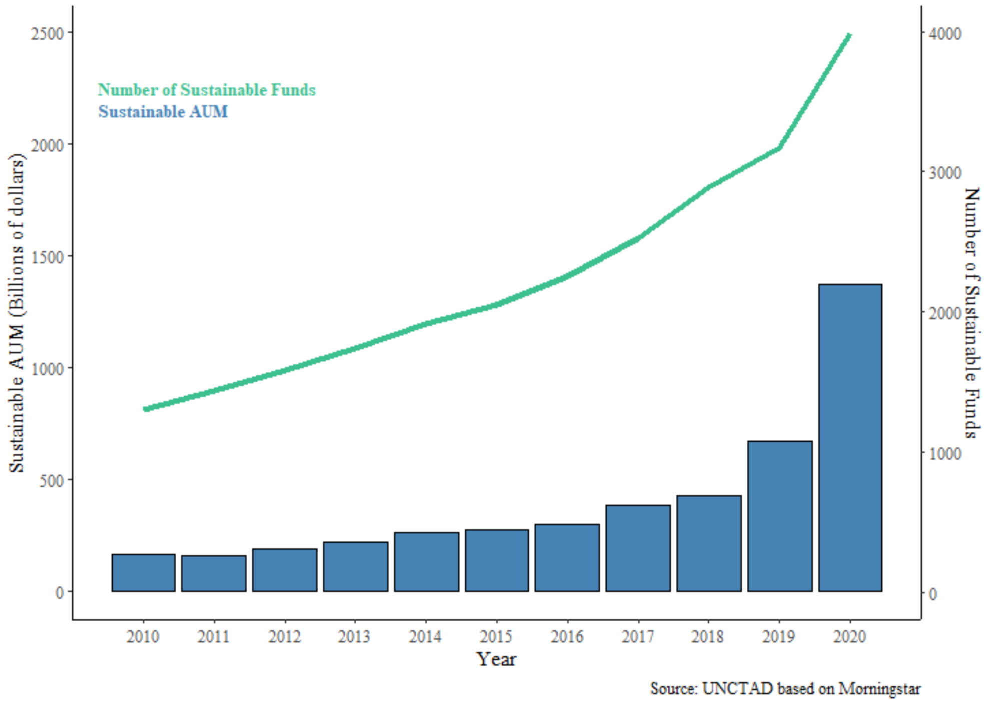

Figure 2.2: Number and AUM of Sustainable Funds

Considering Figure 2.2, which shows that sustainable investors have become trendier, it is natural to think that companies that engage in green innovation can attract more investors. Robert Merton shows with his capital market equilibrium model that increasing the size of the company's investor base will reduce the cost of capital and, at the same time, increase the company's value. Thus, in Merton's model, he proves that a firm manager has the incentive to expand the investor base (Merton, 1987).

Like Merton, Heinkel et al. (2001) also developed an equilibrium model building on Merton's findings. However, they studied the effect of the cost of equity with the exclusion of high-polluting firms. They argue that "green" investors will only invest in companies that contribute to more environmentally friendly solutions. In contrast, "neutral" investors will invest in all opportunities that would give a financial return. Therefore, when polluting firms are only held by "neutral" investors, they will experience a reduction in the investor base. As a result, investors in high-polluting firms need to increase their ownership and would therefore demand a higher return to compensate for the decreased risk sharing.

Furthermore, based on European firms, Alessi et al. (2021) find that investors accept lower returns to hold greener stocks. In other words, investors are willing to sacrifice potential higher returns in order to invest in companies that have a positive impact on the environment. This finding suggests that green innovation can reduce a company's cost of equity. If investors are willing to accept lower returns to hold greener stocks, these stocks are likely to experience a higher demand. This can lead to a lower cost of equity for companies that prioritize green innovation, as they will be able to attract more capital.

To summarize, responsible investors are relevant for the relationship between green innovation and the cost of equity because they are willing to pay a premium for a company's equity if the company provide environmental benefits. This will attract more capital, and likely result in lower cost of equity.

2.4 Risk Channel

As mentioned in Section 2.2, we identified that green innovation can affect the cost of equity through risk. In this section, we have identified three channels where green innovation can reduce risk 1) transition risk and 2) credit risk and 3) systematic risk.

First, the Financial Stability Board claims that transition risk is a factor more investors should consider (Financial Stability Board, 2020). Transition risk is related to the transition to a net zero world. The risk particularly includes adapting to new regulations and policies. These can be costs such as carbon tax and emission trading systems (ETS). In addition, it may be fiscal politics that supports innovation for low-carbon technologies (NBIM, 2021b). For example, the percentage of greenhouse gas (GHG) emissions covered by emission prices has increased significantly in recent years (The World Bank, 2022). Figure 2.3 shows that in 2000 only 0.44% of global GHG emissions were covered by a carbon pricing scheme, compared to 23.17% in 2022.

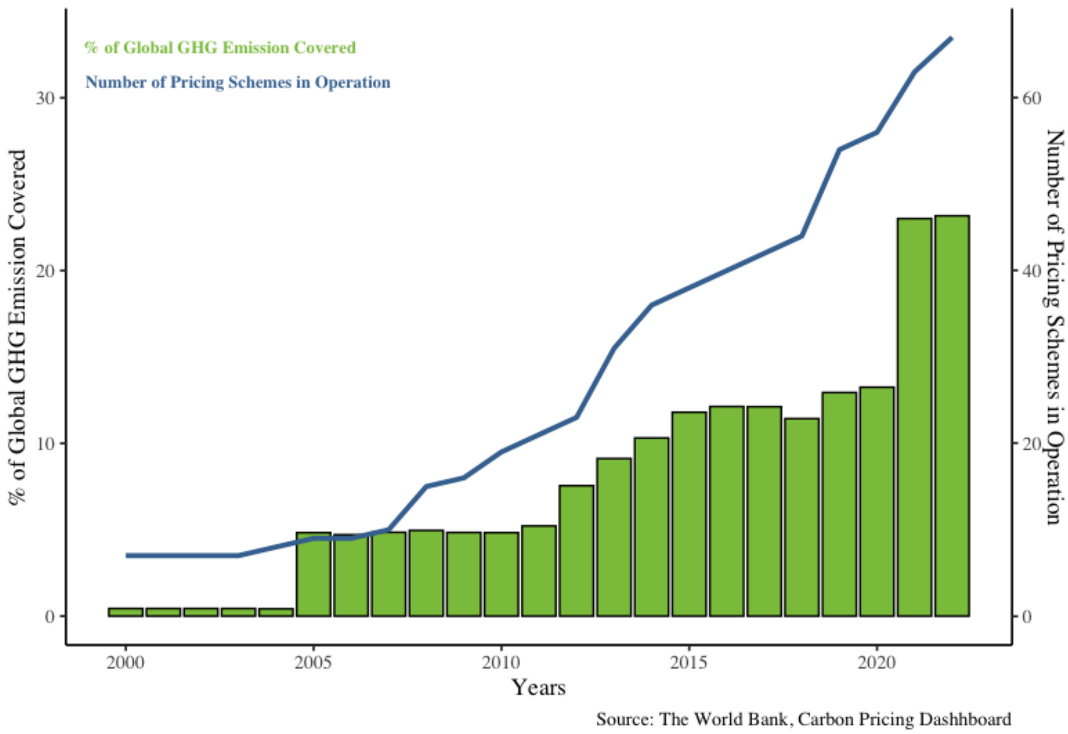

Figure 2.3: Greenhouse Gas Emissions Coverage

Furthermore, green innovation can help a firm reduce the transition risk, and are technologies that control, reduce or prevent emission of GHG. Kim et al. (2015) use greenhouse gas emission data to investigate the carbon risk effects on the cost of equity. With the use of carbon intensity (emission/sales) as a proxy for carbon risk, they found that it is positively correlated with the cost of equity. They conclude that firms' efforts to reduce carbon emissions are compensated by a decrease in the cost of equity (Kim et al., 2015).

Second, there is increasing evidence that firms who prioritize and engage in green innovation may reduce the overall risk of the firm. A study by Carbone et al. (2021) found that companies with high emissions tend to have higher credit risks and are more likely to default. Furthermore, Gutierrez-Lopez et al. (2022) found that transitioning to a low-carbon economy leads to a greater distance to default, and that innovation enlarges the distance to default. Together, these studies demonstrate the importance of green innovation in reducing a firm's credit risk.

Third, Sharfam & Fernando (2008) found that the financial markets reward companies that implement strategies to improve their environmental risk. The main benefit is a reduction in the cost of equity, particularly through lower stock volatility as measured by beta. Since green innovations are technologies that control, reduce or prevent the emission of GHG, companies can reduce their environmental risk through green innovation activities. Overall, reducing the firm's beta will result in a lower cost of equity, as seen in equation 2.1.

To summarize, green innovation can provide several benefits in the risk channel. Reducing environmental impact with green innovation, companies can decrease their equity cost by avoiding regulatory fines, reduce credit risk, and reducing their stock volatility.

3 Hypothesis

In this chapter, we present our hypothesis. Throughout the literature review, we identified two channels where higher green innovation could lead to a lower cost of equity:

1. Investor Base Channel

   Firms proving their environmental commitment can attract more and cheaper capital from the growing base of environmentally responsible investors (Heinkel et al., 2001). Moreover, green patents can be a credible signal of a firm's environmental commitments (Berrone et al., 2015). Therefore, investing in green innovation can make a company more attractive to these investors and lead to an increased stock demand and larger investor base.

2. Risk Channel

   Green innovation can help reduce risk by enabling companies to adapt to new environmental regulations and market conditions. Kim et al. (2015) proved that lowering transition risk would result in a lower cost of equity. Furthermore, Gutierrez-Lopez et al. (2022) proved that green innovation enlarges the distance to default and Sharfam & Fernando (2008) found that improving environmental risk would lower stock volatility.

Based on the two arguments, our hypothesis is:

There is a negative relationship between green innovation and the cost of equity

4 Data

In this chapter, we explain the data preparation for the quantitative analysis. We describe our data sources and explain the process of gathering and tidying the data.

4.1 Data Selection

The sample is limited to public European companies. To examine the relationship between green innovation and the cost of equity, we use six databases: (1) The Refinitiv Eikon database, which provides financial data, (2) Bloomberg Terminal, which provides the cost of equity, (3) DataStream, which provides I/B/E/S analyst forecasts to calculate implied cost of equity, (4) OECD database, which provides country-specific data like GDP and the risk-free rate, (5) OECD Patent database, which provides patent application data, (6) ORBIS database, which provides data on subsidiaries.

The sample consists of data from year 2000 until 2019 for the 500 largest publicly traded firms in Europe per 01.08.2022.

4.1.1 Patent Data

As our analysis is of European companies, it is relevant to investigate patent applications filed to the European Patent Office (EPO). The EPO examines European patent applications for a total of 39 countries, including all 27 EU member states and countries like Norway and Switzerland (EPO, 2022b). There are different ways to obtain a patent through EPO, and they classify three diverse routes. (1) National route, an inventor can protect the innovation by filling an application to the national patent office. (2) International route, file their application through the Patent Cooperation Treaty (PCT). (3) Regional route, apply for application directly to the EPO (OECD, 2009).

Our source for the patent data is the EPO Worldwide Statistical Database, gathered from the OECD's Directorate for Science, Technology, and Innovation. Their database covers all applications through the three routes mentioned above, and they have data on patent applications back to the late 1970s, and their data is right up until august

2022. However, the publication of the patent application generally takes place 18 months after the first filing (OECD, 2009). Therefore, we exclude year 2021 and 2020 and limit our sample from year 2000 to 2019. The EPO only handles patent applications that are considered valuable enough to warrant international protection (IEA, 2021b). This helps ensure the quality of the patent applications and as our sample consists of the largest public companies in Europe, we assume they are familiar with the application process and the cost it entails. Thus, they only apply for patents with a realistic probability of being granted and considered innovative. Additionally, we use citations as our main proxy for patent innovation which represent patents that have been granted.

The patent data we use in our analysis have been extracted from three different OECD databases:

1. OECD REGPAT database from august 2022. The REGPAT database presents data such as applicant name, country, date, and a classification code to address the type of patent (OECD, 2008).
2. OECD HAN database from august 2022. The HAN database delivers a database with the patents grouped by clean applicant names.
3. OECD CITATIONS database from august 2022. The CITATIONS database provides information on citations on all the different patents for PCT, EPO, and the United States Patent and Trademark Office.

4.1.2 Classification of Green Patents

Whether a patent is “green” or not might seem diffuse, but there are two main ways to classify a patent: The Cooperative Patent Classification (CPC) and the International Patent Classification (IPC). The IPC is established by the World Intellectual Property Organization (WIPO). The CPC is a partnership between EPO and the United States Patent and Trademark Office (USPTO), and is an extension of the IPC (EPO, 2022a).

We use CPC, because they have more precise definition of green patents. Green patents are applications classified under the category Y02: Technologies or Applications for mitigation or adaption against climate change. This category includes technologies that control, reduce or prevent emissions of greenhouse gases in accordance with the Kyoto Protocol and the Paris Agreement (Espacenet, 2022). CPC further classifies Y02 into eight more detailed sub-categories. The classification is explained in more detail in appendix A1.

4.2 Data Processing

This section explains how we prepared the data before the analyses.

4.2.1 Combining Patent Data

The three relevant OECD databases are merged, and the information needed for the following processing is selected. This includes application id, application number, application name, citation count, and technology classification codes.

The first step of the process is to merge applications from EPO and PCT, and after removing duplicates, the dataset consists of around 6 million rows. It is essential to account for duplicates since most patent applications through EPO are also filed through PCT. Furthermore, after classifying all applications using the CPC scheme and selecting relevant years, our final patent application dataset counts 4.7 million applications.

4.2.2 Merging Firm-Specific and Patent Data

The most demanding part of data processing is to match the patent data with firms. Unfortunately, there are no unique Firm-ID in OECD's patent databases. This makes the matching process complex, and if not done thoroughly, it can introduce bias and errors in the data.

The applicant's name is the only indicator of who has applied for the patent. However, this name is written manually and is subject to misspellings and a considerable variation of company names. Several situations have arisen with misspellings and variations in company names. Meaning manual work is required to check that the data was correct.

Additionally, applicants filed by subsidiaries are another challenge because these names might not be associated with their parent company. Some large firms have subsidiaries specialized in patent applications and can even be located in a country other than the parent company (OECD, 2009). Therefore, it is essential to account for subsidiaries to avoid creating noise in the data. For example, Equinor ASA rarely appears as "Equinor" in the data, but one of their many subsidiaries, for example, "Hywind AS". Applicants filed under a name not linked to the parent's name are difficult to find. OECD recommends matching patent data to an external company database with information on subsidiaries (OECD, 2009). Therefore, we gathered a list of 30 000 subsidiaries from ORBIS to find all patent applications relevant for a company.

Finally, we used a Python script to process the large patent dataset and match the data with our list of company names, including subsidiaries. The script also matched the names to both the applicant's and OECD's standardized names. Once the script was finished, we manually validated the matches to avoid incorrect matches.

4.2.3 The Final Sample

After matching all the patent data with the firms in our sample, the final sample consists of 417 of the 500 largest public companies in Europe, from 22 different countries. With a total of 598 768 patents. Figure 4.1 provides an overview of the countries with the highest green share (Green Patents/Total Patents), and we can spot that Portugal, Spain, Denmark and Poland are the nations with the highest green share in our sample. This is linked to the countries having energy- and utilities companies in our sample, and as seen in Table 4.1 these industries have a high green share. Additionally, it does not mean that all countries colored in "grey" do not engage in innovation but that they do not have large enough companies to enter our sample.

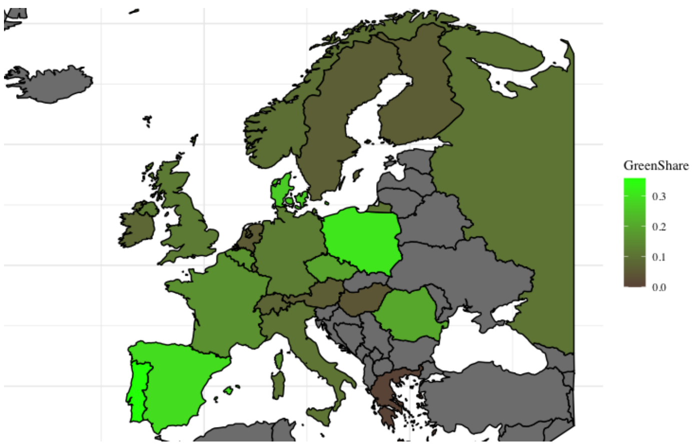

Figure 4.1: The map shows the green share of patents in countries from our sample. Countries with few companies are highly affected by the industries the companies are in.

Furthermore, table 4.1 presents the number of green patents of the different industries based on their total number of green patent applications in the period 2000-2019. Also, the table presents the total number of patent applications, the green share, and the number of companies in our sample from each industry. The table displays that the Industrial industry has most patents, both in total and in green patent applications. However, although having the most green patents, green share for the Industrials industry is 12%, and similar to the mean of the whole sample. The Energy industry has an average green share of 28%, only lower than the Utilities sector.

Table 4.1: The table shows the number of green patents, total patents, the green share, and the number of firms in each industry. The data is from 2000 to 2019 and includes 417 of the largest public European companies.

Rank	Industry	Green Patents	Total Patents	Green Share	Firms
1	Industrials	25,778	175,751	0.12	88
2	Consumer Discretionary	13,381	85,441	0.09	54
3	Basic Materials	6,811	50,412	0.14	35
4	Energy	6,655	21,368	0.28	25
5	Health Care	5,749	123,255	0.03	41
6	Telecommunications	3,349	78,172	0.03	15
7	Utilities	2,188	6,757	0.30	22
8	Technology	1,200	20,255	0.06	16
9	Financials	1,096	13,188	0.08	71
10	Consumer Staples	869	23,154	0.07	33
11	Real Estate	71	1,015	0.08	17
	Total	67,147	598,768	0.12	417

The raw sample consists of 8,646 firm-year observations. We require no missing values for Total assets, Market capitalization, Debt to equity ratio, and Book value of equity, and after excluding N/A values, the sample counts 7,881 firm-year observations. Furthermore, we only included companies that had at least one patent application during the period. When retrieving the cost of equity from the Bloomberg Terminal, we also get some missing values. The final sample then consists of 6,790 observations and 417 companies. We use the Industry Classification Benchmark (ICB) to classify our companies into different industries. The ICB is a scheme for classifying all public companies into 11 different industries based on their primary source of income (FTSE Russell, 2022). A table describing each industry can be found in appendix A1.

5 Methodology

In this chapter, we present the methodology applied for our regression models. We first present the variables included in the analyses. Then we present the model specification, and finally we elaborate on relevant tests to validate our model.

5.1 Selection of Variables

5.1.1 Dependent Variable: Cost of Equity

There are several ways of calculating the cost of equity (COE). The most used model to estimate the COE is as mentioned, the CAPM, by Treynor (1961) and Sharpe (1964). We have used Bloomberg´s calculated COE based on the CAPM model.

$$COE = r_f + \beta \times (R_m - r_f) \tag{5.1}$$

Where:

COE = Cost of Equity
r_f = Riskfree rate
β = Asset risk compared to market
R_m = Market rate of return

The risk-free rate for each stock is the local government 10-year bond. Bloomberg estimated beta (β) with a regression analysis of each stock's weekly return on the local market over the last five years as standard. The market rate of return describes the expected return from the stocks home market. The Bloomberg market rate of return is more complex than just the average of the stock's home market, they also add indexes that take the industrial average into account.

CAPM is a widely used financial academic model, but have been found, as other academic models, to have weaknesses. The main limitation of the CAPM is that it relies on historical data to calculate expected returns and risk. For example, Fama & French (1997) exposed with their three-factor model the weaknesses of CAPM. The main weaknesses being the large standard errors and the uncertainty surrounding the risk premium. Therefore, they conclude that these estimates of the COE using the CAPM may not be precise enough (Fama & French, 1997).

After the criticism against the CAPM, research has been done on the COE. Recently there have been several versions of the dividend discount model. This model is not based on risk, like CAPM, but uses future dividends as the biggest factor. We have also calculated the implied COE to ensure our results are robust. The implied COE is a more advanced version of the simple dividend discount model. There are several different models, and the most used are the models from Easton (2004) and Ohlson & Juettner-Nauroth (2005). However, these models do also have limitations, and they are dependent on the analyst's forecast measurements. Therefore, like Hail & Leauz (2006) we average the models to reduce potential forecast bias and measurement errors. For the sake of brevity, the model's calculation can be found in Appendix A2.

5.1.2 Explanatory Variable: Green Innovation

There is no standard to measure how innovative a company is. Looking back at previous research, they have chosen to use both the number of green citations and the number of green patents. As mentioned in the literature review, we follow Trajtenberg (1990) in using green patent citations as the explanatory variable.

Furthermore, Ernst (2001) shows that there is a time-lag between the patent application and the economic effect, and therefore we use the lagged value of green patent citations to get a more accurate estimate of the environmental impact of a patent. Lagging the green innovation measure takes into consideration the time it takes for a green patent application to have an impact on the firm's environmental and financial performance (OECD, 2009). Since our arguments are based on the environmental impact of green innovation, it is reasonable to lag the explanatory variable, to better capture the environmental impact of green patents.

Finally, we follow previous studies on patents like Bloom & Reenen (2002), Elmawazini et al. (2022) and Hea & Tian (2013), and take the natural logarithm of patent citations, and in our case, the logarithm of green citations. Furthermore, we check the robustness of our regression model with the logarithm of green patents and green share. Green share is defined as the number of green patent applications divided by the number of total patent applications (Hao et al., 2021), for each respective company and year.

5.1.3 Control Variables

In our regression analysis, we use control variables as prior studies. These variables have been shown to affect the COE significantly, and we have mainly taken inspiration from El Ghoul et al. (2011) and Elmawazini et al. (2022).

Size

Based on previous studies, like Fama & French (1992), the findings indicate that size is expected to have a negative relationship with the COE. Moreover, Bloomfield & Michaely (2004) reported that professionals expect larger firms to be less risky. Therefore, we expect size to have a negative effect on COE. We follow previous studies on COE like El Ghoul et al. (2011), and measure the company's size by taking the natural logarithm of the firm's total assets.

Book-to-market ratio

Fama & French (1992) shows that book to market ratio is a good measure to explain the average return of a stock. Fama & French (1995) also states that the book-to-market estimate works as a measurement to see if companies can become financially distressed, as companies with a high book-to-market tend to feel financial distress. Gode & Mohanram (2003) argues that a high book-to-market ratio could reflect lower growth opportunities, lower accounting conservatism, or high perceived risk. Based on this, we expect the book-to-market ratio to have a positive relationship with the COE.

Beta

Beta is a measure of systematic risk, which tells us how the stock varies in relation to the stock market. We use the beta from Bloomberg, as mentioned, calculated as a regression of the weekly return on each stock's local market return over the last five years. An investor would compensate a riskier asset with a higher COE. Therefore, we expect a positive relationship between the COE and beta.

Leverage

We measure Leverage as Debt over Equity. Modigliani & Miller (1958) was one of the first with a theory based on capital structure and the COE. Their second proposition states: "The cost of capital of levered equity increases with the firm's market value debt-equity ratio" (Berk & DeMarzo, 2016, p. 531). They argue that the company's COE is proportional to the company's leverage level. An increase in debt leads to a higher risk for the shareholders. Therefore, it is expected that leverage has a positive relationship with the COE.

Total Patents

We include total patents as a control variable in our analysis because it will likely affect both green innovation and the COE. By controlling for total patents, we avoid confounding the results with the effects of other types of innovation. Moreover, more innovation can increase a firm's competitiveness but at the same time also increase its risk. As we follow previous research and take the logarithm of green citations and patents, total patents is also measured as the natural logarithm.

Country-level control variables

Changing economic conditions on the country level can lead to differences in financing and investment. Therefore, we include GDP per capita as a control variable for the country's economic development. Following El Ghoul et al. (2018), we expect GDP to have a negative effect on COE. Moreover, we follow El Ghoul et al. (2018) and take the natural logarithm of GDP.

5.2 Model Specification

To examine the relationship between green innovation and firm's COE we apply five regression models with several firm-level control variables, as well as country-level controls, and different fixed effects.

Deciding which fixed effects to use, depends on whether there are unobserved effects that can cause a correlation between our dependent and explanatory variable. Year- and industry-fixed effects are included to control for the fact that we have multiple observations across different years and industries. Visual arguments for choosing year- and industry-fixed effects can be found in appendix A4. We apply year-fixed effects to control for time-varying factors which could affect COE. For example, changing macroeconomic conditions throughout the period. Industry-fixed effects are included since it can effectively control for time-invariant characteristics of an industry that affects COE. For example, differences in regulations and competitiveness. Moreover, Table 5.1 suggest that there are large variation of green innovation across industries.

Furthermore, to increase the robustness of the results we also include regression models with country-fixed effects and country-year-fixed effects. Country-fixed effects are included to capture time-invariant characteristics of a country that affects COE. Further, we include country-year fixed effects to control for year-specific country effects.

We do not use firm-fixed effects because of the risk that the firm-fixed effects remove the cross-sectional variation when firm attributes change slowly over time (Zhou, 2001). Assuming the relationship between green innovation and COE is driven by cross-sectional rather than time-series variation. In that case, firm fixed effects could absorb green innovation's effect on the COE. When using Bloombergs CAPM COE which is calculated from historical data as discussed in Section 5.1.1, the variation across time is limited.

The variables in the models presented on the next page can be found in Appendix A3. The inclusion of the fixed effects allows us to better understand the relationship between green innovation and COE.

In model (1), we develop a OLS regression without fixed effects to understand the relationship between green innovation and cost of equity without fixed effects.

$$\begin{aligned} COE_{it} = {} & \beta_1 log(GreenCitations_{it-1}) + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \beta_4 BTM_{it} \\ & + \beta_5 Beta_{it} + \beta_6 log(TotalPatents_{it-1}) + \beta_7 log(GDP_{it}) + \epsilon_{it} \end{aligned} \tag{5.2}$$

In model (2), we include year fixed effects λ, by year t.

$$\begin{aligned} COE_{it} = {} & \beta_1 log(GreenCitations_{it-1}) + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \beta_4 BTM_{it} \\ & + \beta_5 Beta_{it} + \beta_6 log(TotalPatents_{it-1}) + \beta_7 log(GDP_{it}) + \lambda_t + \epsilon_{it} \end{aligned} \tag{5.3}$$

Further, Model (3) adds industry fixed effects μ, by industry j.

$$\begin{aligned} COE_{it} = {} & \beta_1 log(GreenCitations_{it-1}) + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \beta_4 BTM_{it} \\ & + \beta_5 Beta_{it} + \beta_6 log(TotalPatents_{it-1}) + \beta_7 log(GDP_{it}) + \lambda_t + \mu_j + \epsilon_{it} \end{aligned} \tag{5.4}$$

Model (4) further adds country fixed effects δ, by country c.

$$\begin{aligned} COE_{it} = {} & \beta_1 log(GreenCitations_{it-1}) + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \beta_4 BTM_{it} \\ & + \beta_5 Beta_{it} + \beta_6 log(TotalPatents_{it-1}) + \beta_7 log(GDP_{it}) + \lambda_t + \mu_j + \delta_c + \epsilon_{it} \end{aligned} \tag{5.5}$$

Finally, in model (5), we include country-year fixed effects ρ, by country c and year t.

$$\begin{aligned} COE_{it} = {} & \beta_1 log(GreenCitations_{it-1}) + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \beta_4 BTM_{it} \\ & + \beta_5 Beta_{it} + \beta_6 log(TotalPatents_{it-1}) + \beta_7 log(GDP_{it}) + \lambda_t + \mu_j + \delta_c + \rho_{ct} + \epsilon_{it} \end{aligned} \tag{5.6}$$

5.3 Model Testing

Since the fixed effects regression is a form of OLS regression, some assumptions must be satisfied. The relevant tests to examine the assumptions are included in appendix A5. To summarize, we make some adjustments to our model. The adjustments include clustered standard errors, log transformation of some variables, and elimination of extreme outliers. We cluster standard errors at firm level to mitigate biases from heteroskedasticity and autocorrelation, following Petersen (2009) and Hail and Leuz (2006). Clustering standard errors at the firm level allow for correlation within multiple observations of a given firm.

Furthermore, extreme outliers that are not representative of the full sample could lead to wrong conclusions. Therefore, balance sheet data is winsorized at 1 and 99 percentiles to minimize the effect of potential outliers. Furthermore, it is difficult to conclude whether the zero conditional mean assumption is satisfied. However, based on the tests in the appendix Section A5, we recognize the model as acceptable but suggest that one should be careful with interpreting the results as causal.

6 Empirical Analysis

This chapter is divided into three parts, where Section 6.1 presents summary statistics. Further, Section 6.2 discuss the results from our main model specification, which tests green innovations' effect on the COE. In Section 6.3, we apply a robustness check with different measures of green innovation and COE. Additionally, we test for endogeneity using a 2SLS regression. Finally, in Section 6.4 we discuss the results and compare to the findings of Elmawazini et al. (2022).

6.1 Summary Statistics

In this section, we present summary statistics of our data used to analyse the relationship between green innovation and the COE. Section 6.1.1 presents descriptive statistics, while Section 6.1.2 presents a correlation matrix. Further, Section 6.1.3 provides descriptive statistics of companies with high and low green innovation efforts. Finally, Section 6.1.4 presents the yearly average COE for the average company with high and low green innovation efforts, from year 2000 until 2019.

6.1.1 Descriptive Statistics

We provide two descriptive statistics tables. The first table presents the variables as used in the regressions, while the second includes actual numbers of the variables which are not log-transformed. This is done to show how log-transformation of some of the variables may impact the results. Table 6.1 and Table 6.2 provides descriptive statistics of the COE and all the independent variables in our sample of 417 of Europe's 500 largest companies between year 2000 and 2019. The table includes mean, standard deviation, and minimum and maximum values for the variables.

On average, the COE is 10.1%, and a firm has about 9 green patents and 35 green citations per year.

Table 6.1: Descriptive statistics for 6,790 firm-year observations from 2000 to 2019. The table shows the mean, standard deviation, minimum, maximum, and observation count for the variables COE (cost of equity), Beta, BTM (book-to-market ratio), Leverage (debt-to-equity ratio), Size (natural logarithm of total assets), GDP (natural logarithm of GDP per capita), Total Patents (natural logarithm of total patents), Green Patents (natural logarithm of green patents), GreenShare (green patents divided by total patents), and GreenCitations (natural logarithm of the number of citations a firm receives for its green patents)

Statistic	N	Mean	St. Dev.	Min	Max
COE	6,790	10.1	3.0	3.05	33.7
Beta	6,790	0.9	0.3	−0.04	2.7
BTM	6,790	60.4	40.9	11.1	162.9
Leverage	6,790	92.6	90.9	3.6	363.2
Size	6,790	23.5	1.8	20.5	27.0
GDP	6,790	10.6	0.3	8.9	11.7
GreenShare	5,562	10.1	19.8	0.0	100.0
TotalPatents	6,790	2.58	1.90	1.0	8.69
GreenPatents	6,790	0.93	1.29	0.0	6.78
GreenCitations	6,790	1.41	1.86	0.0	7.99

Table 6.2: Descriptive statistics for 6,790 firm-year observations from 2000 to 2019. The table shows the mean, standard deviation, minimum, maximum, and observation count for the variables Size (Total Assets reported as billion USD), GDP (GDP per capita reported as thousand USD), Total Patents, Green Patents, and Green Citations (total number of citations a firm receives for its green patents).

Statistic	N	Mean	St. Dev.	Min	Max
Size	6,790	67.6	128.4	0.8	511.0
GDP	6,790	40.8	11.9	6.4	11.9
TotalPatents	6,790	82.8	287.0	1.0	5,934.0
GreenPatents	6,790	9.2	39.5	0.0	883.0
GreenCitations	6,790	34.9	142.5	0.0	2,937.0

6.1.2 Correlation Matrix

The correlation coefficients in Table 6.3 suggests low correlation between the independent variables, which suggests that multicollinearity is unlikely to be a concern. However, there is one exception. There is strong correlation between the control variable, total patents, and the explanatory variables green patents and green citations. However, the multicollinearity is tested through a VIF test in appendix A5.4, suggesting that multicollinearity won't be a problem. The correlation between the COE and our green innovation measure is positive, which is inconsistent with our hypothesis. However, when researching our hypothesis, we must control for other considerations to isolate green innovations' effect on the COE. Therefore, in our main regression, we include control variables, and different fixed effects.

Table 6.3: Correlation matrix showing the relationship between dependent and independent variables. The table displays the correlation coefficients between the variables COE, GreenCitations, GreenPatents, GreenShare, TotalPatents, Beta, BTM, Leverage, Size, and GDP.

	COE	GreenCitations	GreenPatents	GreenShare	TotalPatents	Beta	BTM	Leverage	Size	GDP
COE	1	0.11	0.13	0.14	0.05	0.74	0.30	0.15	0.29	0.03
GreenCitations	0.11	1	0.95	0.84	0.74	0.18	0.03	-0.07	0.21	0.07
GreenPatents	0.13	0.95	1	0.85	0.76	0.21	0.04	-0.06	0.23	0.09
GreenShare	0.14	0.84	0.85	1	0.48	0.17	0.10	-0.04	0.19	0.05
TotalPatents	0.05	0.74	0.76	0.48	1	0.17	-0.09	-0.08	0.18	0.103
Beta	0.74	0.18	0.213	0.17	0.17	1	0.25	0.13	0.33	0.15
BTM	0.30	0.03	0.04	0.10	-0.09	0.25	1	0.11	0.40	-0.08
Leverage	0.15	-0.07	-0.06	-0.04	-0.08	0.13	0.11	1	0.39	-0.07
Size	0.29	0.21	0.23	0.19	0.18	0.33	0.40	0.39	1	0.02
GDP	0.029	0.07	0.09	0.05	0.10	0.15	-0.08	-0.07	0.02	1

6.1.3 Average Green & Brown Company

Table 6.4 provides descriptive statistics of the COE and all the independent variables for companies with high (green) and low (brown) levels of green innovation. In contrast to the descriptive tables (6.1 & 6.2) for the full sample, Table 6.4 represents firms instead of observations. The table also includes the difference in means and t-statistics.

The descriptive statistics suggest that companies with higher green innovation efforts have higher COE. Green companies have, on average, a COE of 10.4%, compared to 9.9% for brown companies. The T-Stat indicates that green companies have significantly higher COE. As with the correlation between green innovation and COE this is inconsistent with our hypothesis.

Table 6.4: Descriptive statistics for companies with high and low levels of green innovation. The table shows the mean, standard deviation, minimum, maximum, and observation count for the variables COE, Beta, BTM, Leverage, Size, GDP, TotalPatents, GreenPatents, GreenShare, and GreenCitations. The table also shows the difference between the means and t-statistics for companies with high and low levels of green innovation.

	$GreenInnovation > Median$					$GreenInnovation < Median$						
	N	Mean	St. Dev.	Min	Max	N	Mean	St. Dev.	Min	Max	Diff	T-Stat
CoE	208	10.4	1.7	4.3	15.1	209	9.9	1.9	5.0	16.0	0.5	2.29^{**}
Beta	208	0.9	0.2	0.4	1.4	209	0.9	0.2	0.4	1.4	0.0	0.37
BTM	208	66.6	32.2	11.5	141.9	209	52.7	32.4	12.2	162.9	13.9	3.56^{***}
Leverage	208	89.7	74.6	3.6	363.2	209	95.2	78.2	3.6	363.2	−5.5	1.42
Size	208	23.7	1.6	20.5	27.0	209	23.2	1.8	20.5	27.0	0.5	2.24^{**}
GDP	208	10.6	0.3	9.7	11.4	209	10.6	0.2	9.8	11.0	0.0	0.15
Green Share	208	20.0	19.8	10.0	1.0	209	2.0	2.0	0.0	10.0	18.0	11.65^{***}
Total Patents	208	1,561.5	5,615.2	1.0	72,726.0	209	1,195.8	4,310.8	1.0	40,549.0	365.7	1.10
Green Patents	208	268.8	866.7	1.0	10,316.0	209	43.0	205.2	0.0	2,212.0	225.8	2.24^{**}
Green Citations	208	1,014.0	3,152.6	0.0	34,878.0	209	163.1	739.3	0.0	8,012.0	850.9	4.15^{***}

6.1.4 Cost of Equity over Time

Figure 6.1 displays the yearly average COE for green and brown companies from 2000 to 2019. The two groups of companies follow a similar trend, and as expected after the descriptive statistics, the COE for green companies is higher throughout the period. However, it is not easy to draw any conclusions from the descriptive statistics, as industries with green companies may have, on average, a higher cost of equity than industries with brown companies. This would mean that the observed differences in the mean COE for companies with high and low levels of green innovation may not be directly related to their level of green innovation but to their industries.

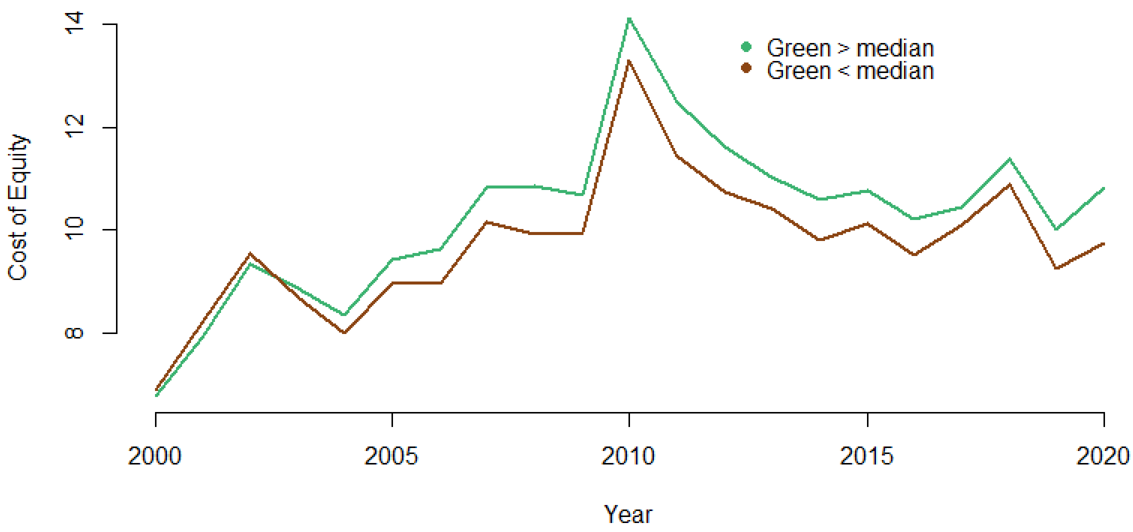

Figure 6.1: Cost of Equity from year 2000 to 2020 for companies with high and low levels of green innovation

6.2 Main Empirical Analysis

This section presents the main results of our thesis, specifically the relationship between green innovation and COE. Our hypothesis is that there is a negative correlation, meaning the coefficient of green citations is statistically significant negative. In Table 6.5, the 5 models proposed in Section 5.2 are presented. The models varies in degree of fixed effects. In models (2) to (5) the following fixed effects are added in ascending order; year, industry, country, and country-year-fixed effects. Additionally, in all models the standard errors are heteroskedasticity-robust and clustered at firm level.

The regression model (1), with no fixed effects, indicates that the coefficient on green citations is positive and statistically significant at the 10% level. Moreover, in model (2), year-fixed effects are added to the regression model. The negative coefficient in this model indicates that green citations has a negative effect on the COE when we control for year-specific effects. This effect is statistically significant at the 10% level.

Furthermore, the negative coefficient in regression (3) indicates that green citations is associated with a lower COE when we control for year- and industry-fixed effects. Moreover, the coefficient of green citations suggests that if a firm increases the number of citations on their green patent by 20%, the cost of equity decreases by 0.01 percentage points. The coefficient is significant at the 5% level. Additionally, when we add a control for country-fixed effects in the regression model (4), the coefficient suggests that green citations negatively affect the COE, which is statistically significant at the 10% level.

After controlling for country-year-specific effects, our findings suggest that green citations do not have a statistically significant effect on COE. All these fixed effects together consume a lot of variation, which might disguise whether green citations significantly affect COE. However, regression model (5) decreases the robustness of the findings in models (2) to (4).

Furthermore, we find that the effects of our control variables are consistent with prior research on COE. Therefore, firms of smaller size, firms with a higher beta, firms with higher leverage, firms with higher book-to-market ratio, and firms in countries with lower GDP have higher COE.

To summarize, the results suggest that green innovation matters for the cost of equity, but the effect is small. Models (2) to (4) show that green citations are significantly associated with a lower cost of equity. Moreover, this is consistent with our hypothesis. Replacing GDP with country-year-fixed effects to control for country-year-specific factors, the effect of green citations on the cost of equity is not significant, although negative.

Furthermore, as mentioned in Section 5.2, we consider regression model (3) as our main specification, and therefore, we will use this model in the robustness checks. Finally, in the next section, we will test if this model is robust to different measures of green innovation and a different measure of the cost of equity.

Table 6.5: The table presents the results from regression models of the cost of equity (COE) as the dependent variable and the logarithm of the number of green citations on a green patent as the explanatory variable. The sample consists of 6,790 firm-year observations between 2000 and 2019 for 417 of the 500 largest public European companies. Size is the natural logarithm of total assets. Standard errors are heteroskedasticity-robust, clustered by firm. The table includes results for five different models, with varying control variables and fixed effects.

	Dependent variable:				
	COE				
	(1)	(2)	(3)	(4)	(5)
log(Green Citations)	0.04*	-0.04*	-0.05**	-0.04*	-0.02
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Size	0.01	-0.02	-0.04*	-0.05*	-0.03*
	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
Leverage	0.00*	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BTM	0.01***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Beta	7.97***	7.53***	7.58***	7.61***	7.51***
	(0.18)	(0.15)	(0.16)	(0.16)	(0.16)
log(Total Patents)	-0.09***	-0.01	-0.00	0.04	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
log(GDP)	-0.88***	-2.55***	-2.38***	-1.00*	
	(0.15)	(0.21)	(0.23)	(0.57)	
Year FE	No	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes
Country-Year FE	No	No	No	No	Yes
Observations	6,790	6,790	6,790	6,790	6,790
R^2	0.56	0.68	0.69	0.70	0.78
Adjusted R^2	0.56	0.68	0.69	0.70	0.77
Note:			*p<0.1; **p<0.05; ***p<0.01		

6.3 Robustness Check

To test the validity of our results, we run our regression with different measures of green innovation and COE. Additionally, we test for endogeneity through a 2SLS regression using the firms initial value of green citations as instrument variable.

6.3.1 Alternative Measures of Green Innovation

To test if the result from our main regression is robust to different measures of green innovation, we run the regression from Table 6.5, model (3), using different measures. In Table 6.6, model (6), we use the natural logarithm of green patents, and in model (7), we use green share. In both models, the measure of green innovation has a negative and statistically significant effect on COE. The result confirms that our findings are robust to using alternative measures of green innovation.

Furthermore, green share is only significant at the 10% level, while green citations and patents are significant at the 5% level. Additionally, when using green share as a measure of green innovation, all control variables are consistent with prior research on COE at the 5% significance level. Finally, the coefficient of green patents suggests that if a firm increases the number of green patents by 20%, the cost of equity decreases by 0.016 percentage point. If green share increases by 20 percentage points, the cost of equity decreases by 0.026 percentage points.

Table 6.6: Table 6.6 presents results from using alternative measures of green innovation. In model (6) and (7) the logarithm of green patents and green share is used as explanatory variable. The sample consists of 6,790 firm-year observations between year 2000 and 2019 for 417 of the 500 largest public European Companies. Size is the natural logarithm of total assets. Standard errors are heteroskedasticity-robust, clustered by firm.

	Dependent variable: COE	
	log(Green Patents)	Green Share
	(6)	(7)
Green Innovation	-0.08**	-0.0013*
	(0.04)	(0.001)
Size	-0.05*	-0.07**
	(0.03)	(0.03)
Leverage	0.00***	0.00***
	(0.00)	(0.00)
BTM	0.00***	0.00***
	(0.00)	(0.00)
Beta	7.63***	7.62***
	(0.16)	(0.16)
log(Total Patents)	0.02	-0.02
	(0.03)	(0.02)
log(GDP)	-1.70***	-2.13***
	(0.22)	(0.27)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	6,790	5,547
R^2	0.70	0.72
Adjusted R^2	0.70	0.72
Note:	*p<0.1; **p<0.05; ***p<0.01	

6.3.2 Alternative Measure of Cost of Equity

To check whether our main regression results are robust to alternative COE measures, we replace CAPM COE with the implied COE in Table 6.7. The result from the robustness test indicates that green innovation has a positive relationship with COE, which is in contrast with our main regression. Moreover, size have a significantly positive effect on COE, contrasting our results with CAPM COE and prior research.

The results of the robustness check using the implied COE as the dependent variable indicate that the relationship between green innovation and COE is not as strong as in the main analysis. The coefficient for the Green Citations variable is not statistically significant, which means that there is not enough evidence to conclude that there is a relationship between green innovation and the implied COE. This suggests that the relationship between green innovation and COE is different across different measures of COE.

Table 6.7: The table presents results from using Implied COE as an alternative measure of cost of equity as dependent variable. The sample consists of 6,790 firm-year observations between year 2000 and 2019 for 417 of the 500 largest public European Companies. Size is the natural logarithm of total assets. Standard errors are heteroskedasticity-robust, clustered by firm.

	Dependent variable: Implied COE
	(6)
log(Green Citations)	0.12
	(0.08)
Size	0.19**
	(0.10)
Leverage	0.01***
	(0.00)
BTM	0.04***
	(0.00)
Beta	1.45***
	(0.35)
log(Total Patents)	-0.17
	(0.12)
log(GDP)	-1.10**
	(0.50)
Industry FE	Yes
Year FE	Yes
Observations	6,419
R^2	0.41
Adjusted R^2	0.40
Note:	*p<0.1; **p<0.05; ***p<0.01

6.3.3 Endogeneity Test

Our main results, presented in Table 6.5, suggest that green citations have a negative impact on COE. We control for omitted variable bias by using year-, industry-, and country-fixed effects in our analysis. However, some omitted variables may be driving the correlation between green innovation and the COE. Additionally, reverse causality or simultaneity may be present in our results. For example, firms with a lower COE may be more likely to invest in green innovation, leading to a biased relationship between the two variables. We use a two Stage Least Squares (2SLS) estimation to test for endogeneity to address these potential issues. We follow the approach of Attig et al. (2013) and El Ghoul et al. (2016) by using the firm-level initial value of green citations as our instrument variable. Table 6.8 presents the results of the 2SLS regression.

We find that the instrument variable correlates with green citations (0.77), and the weak instrument test shows that the variable sufficiently correlates with the endogenous variable. However, the Wu-Hausman test has a p-value of 0.183, indicating no endogeneity issue. Furthermore, the findings from the 2SLS regression support our initial results, with the effect of green citations on COE remaining significantly negative.

Finally, the 2SLS regression does not provide evidence of endogeneity. However, it is still possible that endogeneity issues influence the relationship between green innovation and COE. We will discuss these potential issues in more detail in section 7.3.

Table 6.8: 2SLS Regression Results: Testing for Endogeneity in the relationship between green innovation and cost of equity. The table also shows a Weak Instrument test and a Wu-Hausman test. The sample consists of 6,790 firm-year observations between year 2000 and 2019 for 417 of the 500 largest public European Companies. Size is the natural logarithm of total assets. Standard errors are heteroskedasticity-robust, clustered by firm.

	Dependent variable:
	COE
log(Green Citations)	-0.09**
	(0.04)
Size	-0.04**
	(0.02)
Leverage	0.00***
	(0.00)
BTM	0.00***
	(0.00)
Beta	7.59***
	(0.09)
log(Total Patents)	0.03
	(0.03)
log(GDP)	-2.39***
	(0.10)
Industry FE	Yes
Year FE	Yes
Observations	6,790
R^2	0.69
Adjusted R^2	0.69
Correlation of IV	0.77
Weak Instrument Test	2353.39
(P-Value)	(0.00)
Wu-Hausman	1.77
(P-Value)	(0.18)
Note:	*p<0.1; **p<0.05; ***p<0.01

6.4 Key Findings

Our primary analysis finds that green innovation leads to a lower COE, as shown by the results of our regression model with year-, industry- and country-fixed effects. However, the relationship becomes insignificant when we include country-year fixed effects. Furthermore, our robustness checks using alternative measures of green innovation support our main findings, but the result is sensitive to the definition of COE. The choice of COE model can substantially impact the results, as the implied COE shows a positive but non-significant relationship with green innovation. Finally, the results of the 2SLS regression indicate that our findings are robust to endogeneity.

We find similarities in our results compared with Elmawazini et al. (2022). Like us, they also find a small negative relationship between COE and green innovation. However, for U.S. public firms they find a three times larger effect of green citations on COE. Different to our thesis, they used a more complex version of the implied COE model as the dependent variable. Due to a lack of access to data, we use CAPM COE and calculate a simpler version of the Implied COE as a robustness test. We get similar results in our main regression with CAPM COE as the dependent variable. However, our model with the implied COE find a positive but insignificant relationship between the variables, which gives conflicting results compared to Elmawazini et al. (2022). It is worth mentioning, in Table 6.7, that the sign of the control variable size contradicts prior research, which indicates that the regression model does not represent the true relationship between size and COE. Without speculating too much, this may also apply to the relationship between green innovation and the cost of equity. Whether we get different results than Elmawazini et al. (2022) because of the simpler calculation of the implied COE or not is difficult to say. However, the robustness test fails, and we can not conclude that there is a clear negative relationship between green innovation and COE.

Overall, the results imply that green innovation can reduce the cost of equity. However, whether this can be explained by larger investor base or reduced risk is rather difficult to conclude. To gain a deeper understanding of the results, the following chapter aims to identify the mechanisms behind them.

7 Mechanism & Discussion

In this chapter, we will explore the mechanism behind the results of the main model and we will mention other potential explanations. Additionally, we will discuss potential endogeneity issues behind our findings.

7.1 Mechanism

In this section, we attempt to discover and discuss the mechanism behind our results in Chapter 6. To empirically analyse if green innovation has a negative impact on the COE because of our suggested arguments, we want to test green innovation's effect on the investor base and risk channel. The suggested arguments are:

1. Green innovation attracts a larger investor base which lowers the cost of equity
2. Green innovation lowers a firm's risk which lowers the cost of equity

7.1.1 Investor Base Channel

There is no universal measure to calculate the investor base. Therefore, we follow two articles, Breuer et al. (2018) and Chichernea et al. (2014), to measure a firm's investor base. Breuer et al. (2018) calculate equity issue as a proxy for the firm's investor base. This is in line with El Ghoul et al. (2017), who use this as a proxy for firms' access to external financing. The calculation of the variable equity issue is presented in appendix A3. Moreover, Chichernea et al. (2014) use the logarithm of the total number of shareholders and analyst coverage. The number of shareholders measures the recognition of a company. Analyst coverage indicates how many analysts follow the company. The argument is that an analyst brings information to potential investors, and the increased information and media coverage would attract more investors. Our selected control variables also follow our previously used variables and include size, leverage and BTM ratio to control for firm characteristics as well as GDP.

As mentioned, it is hard to measure the investor base, but these variables all together should give us an indication. The regressions in Table 7.1 suggest that there is a positive relationship between green innovation and the investor base. However, green citations is only significant on one of the dependent variables, and it is the analyst coverage. This indicates that firms with more green citations would attract more analysts. Furthermore, analysts can increase the visibility of a stock and investors' knowledge about a firm. Thus, reduce asymmetric information, which leads to a reduction in the COE (Merton, 1987).

Table 7.1: The table presents the results of our analysis of the impact of green innovation on equity issues, analysts, and shareholders. We use a sample of 6,917 firm-year observations for 417 of the largest publicly-traded European companies between the years 2000 and 2019. The table reports the coefficients of the regression, along with heteroskedasticity-robust standard errors clustered by firm. We control for industry and year-fixed effects.

	Dependent variable:		
	Equity Issue	Analysts	Shareholders
	(1)	(2)	(3)
log(Green Citations)	0.002	0.01^{*}	0.02
	(0.003)	(0.01)	(0.02)
Size	-0.01^{**}	0.31^{***}	0.45^{***}
	(0.01)	(0.02)	(0.06)
Leverage	-0.00^{***}	-0.00	0.00^{**}
	(0.00)	(0.00)	(0.00)
BTM	-0.00^{***}	-0.01^{***}	-0.00
	(0.00)	(0.00)	(0.00)
Beta	-0.023	0.41^{***}	0.28
	(0.02)	(0.08)	(0.27)
log(GDP)	-0.04	0.77^{***}	-1.94^{***}
	(0.03)	(0.18)	(0.62)
log(Total Patents)	0.00	0.05^{***}	0.11
	(0.00)	(0.02)	(0.07)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	6,917	6,917	1,785
R^2	0.15	0.46	0.54
Adjusted R^2	0.15	0.45	0.53
Note:		*p<0.1; **p<0.05; ***p<0.01	

7.1.2 Risk Channel

To address the risk channel, we follow Breuer et al. (2018), Dijk et al. (2021) and Gutierrez-Lopez et al. (2022). The idea is that green innovation will help the companies remain competitive and avoid regulations. Breuer et al. (2018) examine the impact ESG has on the risk channel using beta. Similarly, we want to assess whether green innovation affects the beta, instead of ESG. With the article from Gutierrez-Lopez et al. (2022), from the literature review, we study if green innovation would reduce credit risk. Finally, the last variable is obtained from Dijk et al. (2021) who provides us with the variable transition risk. We expect that green innovation activities will lead to a lower risk. For the sake of brevity, the formula of transition risk and credit risk can be found in appendix A3.

Table 7.2, show the risk channel regression, where we find no clear answers to the results in the main analysis. Both beta and credit risk indicate a negative relationship with green innovation as expected. Green citations is significantly negative on a 10% level and the findings are similar to Gutierrez-Lopez et al. (2022). With an increase in green citations, the firms would experience a reduction in credit risk, which leads the investors to demand a lower compensation for the risk of investing in the company. Measuring transition risk is also a difficult task, and OECD believes the main challenge to price the transition risk comes from the lack of agreed measuring metrics (OECD, 2021). We find no relationship between the transition risk and green innovation. Transition risk is a under-explored topic, but Bolton & Kacperczyk (2021) finds that investors are already demanding compensation for their exposure to carbon emission risk. This will lead to a higher COE for high-polluting firms as shown by Kim et al. (2015). We find no relationship between the transition risk and green innovation. Meaning that green innovation may currently not influence transition risk.

Table 7.2: This table presents the results of our analysis on the impact of green innovation on the cost of equity through the risk channel. The table reports the coefficients of the regression, along with heteroskedasticity-robust standard errors clustered by firm. We control for industry and year fixed effects.

	Dependent variable: COE		
	Beta	CreditRisk	TransitionRisk
	(1)	(2)	(3)
log(Green Citations)	-0.00	-0.02*	0.02
	(0.00)	(0.01)	(0.02)
Size	0.04***	-0.43***	0.03*
	(0.01)	(0.04)	(0.02)
Leverage	0.00**	-0.01***	-0.00
	(0.00)	(0.00)	(0.00)
BTM	0.00***	-0.02***	0.00*
	(0.00)	(0.00)	(0.00)
log(GDP)	0.02	-0.19	0.22*
	(0.03)	(0.26)	(0.13)
log(Total Patents)	0.01***	0.03	-0.01
	(0.00)	(0.03)	(0.01)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	7,311	6,609	5,046
R^2	0.31	0.51	0.02
Adjusted R^2	0.31	0.51	0.02
Note:			*p<0.1; **p<0.05; ***p<0.01

Overall, the results of the mechanism tests are weak. However, we get the impression that green innovation can positively affect the investor base and negatively affect the firm's risk. The weak results of the mechanism tests is as expected because of the small effect green innovation has on COE. The challenging part of the mechanism test is finding suitable measures of the investor base and risk. Because of the unclear results, we will discuss other explanations in the next section to further understand the relationship between green innovation and COE.

7.2 Other Explanations

There may be other explanations of the result, since our two channels of arguments do not provide a clear picture of how green innovation affects the COE. According to Waddock and Graves (1997) there can be two other explanations, 1) slack resource theory and 2) good management theory.

7.2.1 Slack Resource Theory

The slack resource theory argues that better financial performance of a company results in the availability of slack resources. With the availability of slack resources, the firms can then use these to improve their environmental and social performance (Waddock & Graves, 1997). In this case, firms with excess resources or better financial performance are more likely to engage in green innovation. Both Przychodzen & Przychodzen (2015) and de Azevedo Rezende et al. (2019) have investigated the relationship between financial performance and green innovation. Przychodzen & Przychodzen (2015) found by investigating publicly traded companies in Poland and Hungary that there is a positive relationship between green innovation and return on assets. Building on this paper, de Azevedo Rezende et al. (2019) also finds a positive relationship between multinationals' green innovation and financial performance. In addition, Arena et al. (2017) tested how available organization slack affected green innovation, where they concluded that available slack positively enlarges green innovation. Furthermore, we have tested the relationship between financial performance and green patents in our sample of large European firms. In contrast to the mentioned articles, we do not find a significant relationship between financial performance (return on assets) and the number of green patents. For the sake of brevity, the regression table is provided in appendix A6.

7.2.2 Good Management Theory

Furthermore, the good management theory claims that a company should always try to satisfy its relationship with key stakeholders, which would lead to better financial performance. For example, good employee relations would enhance morale, productivity, and satisfaction (Waddock & Graves, 1997). Zhang & Zhu (2019) finds that companies feel green pressure from customers, and to please them, they need to deliver green products. Fulfilling the customer's green requirements, a company would experience a competitive advantage and better financial performance, which would lead to lower cost of equity.

7.3 Endogeneity Issues

In the relationship between green innovation and the cost of equity there are several potential endogeneity issues. Wooldridge (2012) states three main sources of endogeneity: (1) omitted variables, (2) simultaneity and (3) measurement error. This discussion will mention issues related to the first two, and reverse causality.

As mentioned, one potential reason for endogeneity in this relationship is omitted variable bias, whereby other factors not included in the model could be influencing the relationship between the independent and dependent variables. For example, the level of government support for green innovation, the availability of financing for green innovation, and the cost of implementing green innovations could all potentially influence the relationship between green innovation and the cost of equity.

Simultaneity is an issue if firms that invest in green innovation have a lower cost of equity for reasons that are not controlled for in the regression. For example, the industry of the firm which may affect both the cost of equity and green innovation.

Additionally, in the context of green innovation and the cost of equity, endogeneity can occur through reverse causality. In other words, it is possible that the cost of equity could be influencing the level of green innovation, rather than the other way around. For example, if a company has a high cost of equity, it may be less willing to invest in green innovation because the returns from such investments may not be high enough to satisfy its shareholders. Another explanation, could be that firms with a lower cost of equity can have easier access to financial markets and resources, which, in turn, would enable them to undertake green innovation activities. However, Hall and Lerner (2010) argues that large established companies prefer internal funds for financing innovation. This suggests that the companies in our sample may not invest more in green innovation directly through a lower cost of equity.

Potential solutions for the endogeneity issues mentioned could be to use instrumental variables in the regression, as done in Section 6.3. The 2SLS regression can solve endogeneity issues in the relationship between green innovation and the cost of equity and provide a more robust analysis of the relationship. However, it is important to keep in mind that there might be factors not controlled for in a 2SLS regression which cause a correlation between the variables. We were unable to identify suitable instrumental variables beyond the firms' initial value of green citations. It is possible that other instrumental variables could exist and could potentially improve the model. Additionally, the 2SLS regression assumes that the other independent variables are exogenous, which is unlikely to be the case. For example, leverage is likely to be endogenous because the cost of equity may impact the level of equity relative to debt that a company has.

To conclude, endogeneity is an issue that can be challenging to address in empirical analysis. It can be difficult to identify and control for all factors that may bias the relationship between green innovation and cost of equity. This discussion highlights the challenges of assessing the relationship, as it is unclear whether green innovation affects the cost of equity or the other way around.

8 Conclusion

This thesis investigates the relationship between green innovation and the cost of equity. The final sample consisted of 417 companies with 6,790 observations. The analysis follows prior research and applies a fixed effect model with several control variables and year- and industry-fixed effects. We find that a 20% increase in our green innovation measure is associated with a 0.01 percentage-point reduction in the cost of equity. Our results are robust when using different measures of innovation. The results also remain robust when using the 2SLS regression with the firms initial value of green innovation as instrument variable. However, the results are not robust to using the alternative measure of the cost of equity.

To provide further validity to the findings of our main analysis, we investigate the mechanism behind our results. The findings indicate that green innovation could increase the investor base, especially by attracting more financial analysts. Through a deeper analysis of the risk channel, our findings suggest that green innovation may also have a descending effect on a firm's risk. The regression between green innovation and credit risk has a significant negative relationship, which suggests that green innovation could lead to a greater distance to default. However, further research is needed to fully understand the mechanisms and implications for practitioners and policymakers.

To summarize, our findings do not indicate a clear relationship between green innovation and the cost of equity. This may indicate that investors may not consider actual green innovation efforts when making investment decisions. Comparing our results with previous studies on the effect of ESG/CSR on the cost of equity, they find a more direct relationship. This indicates that market participants are more concerned with green reputation and other sustainability measures than green innovation.

Finally, one must interpret our findings cautiously due to potential endogeneity issues. For example, reverse causality and simultaneity, where firms with a lower cost of equity could be more likely to invest in green innovation. In future research, addressing these endogeneity issues will be necessary.

9 Limitations & Further Research

9.1 Limitations

Gathering the patent data from the OECD is a complex and time-consuming operation. Therefore, we had to limit the total number of extracted companies to 500, where 417 had at least one patent. Other studies that investigate the relationship between the cost of equity and a variable of interest, often have a total of 1000 (+) companies in their final sample. And as previously mentioned, there are several challenges in calculating the cost of equity, but the problem has been reduced by using two different methods.

Additionally, endogeneity is a limitation for the thesis. As mentioned previously, reverse causality in the relationship between green innovation and cost of equity could bias the coefficient. If companies with lower cost of equity invest more in green innovation, then endogeneity will indicate a stronger relationship than it actually is.

Finally, there are several limitations within the final patent sample. First, our processing of patent data required a lot of manual work, which could result in measurement bias. Second, the subsidiaries list from Orbis does not consider historical ownership structures. Therefore, a patent that a company applied before a merger or acquisition will appear for the current owner. Third, there is no universal rule to measure innovation. Patent applications do not cover all inventions, and the quality of the patents can vary. A low-quality patent would not be as beneficial as a high quality one, but this is something we have tried taking into account by using citations. Additionally, patents are just one way to measure innovation and may not capture all of a company's efforts to develop and implement environmentally-friendly technologies. Therefore, the company's share of environmental R&D could be relevant for further research. However, this data is limited and difficult to obtain.

9.2 Further Research

The Paris Agreement and European Green Deal are two recent initiatives that aim to reduce climate change and promote sustainability (European Commission, 2015, 2019). The agreements provide a framework that engages green innovation, which could directly impact the research question. Unfortunately, because we have to reduce the sample to 2019, we need more observations to see the effect of these events. Therefore, it would be exciting to do a similar type of study in the next few years, and it could provide valuable insights into the impact of these agreements. Moreover, there is a small effect in the full sample. Therefore, it would be interesting to compare energy intensive with non-energy-intensive industries. Energy production and consumption cause the most GHG, and it would be interesting to compare. As it is natural to think that investors care more about green innovation in energy-intensive industries, compared to industries like Financials, Real Estate and Health Care.

Furthermore, to get a greater overall impression of green innovation effect on the cost of capital. An extension of our thesis could be to investigate the effect green innovation has on the cost of debt. Several factors affect the cost of debt, and risk is a substantial factor. Therefore, if green innovation reduces a firm's perceived risk, the companies will enjoy a lower cost of debt. In addition, German banks have started using patents as collateral for their loans (Kamiyama et al., 2006), which could also reduce the cost of debt.

Overall, there are many opportunities for further research on the relationship between green innovation and the cost of equity. These studies could provide valuable insights for investors, managers, and policymakers.

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Appendix

A1 Classification

Table A1.1: CPC Classification Codes for Green Patents

Y02	**TECHNOLOGIES OR APPLICATIONS FOR MITIGATION OR ADAPTION AGAINST CLIMATE CHANGE**
Y02A	TECHNOLOGIES FOR ADAPTION TO CLIMATE CHANGE
Y02B	CLIMATE CHANGE MITIGATION TECHNOLOGIES RELATED TO BUILDINGS, e.g. HOUSING, HOUSE APPLICANCES OR RELATED END-USER APPLICATIONS
Y02C	CAPTURE, STORAGE, SEQUESTRATION OR DISPOSAL OF GREENHOUSE GASES [GHG]
Y02D	CLIMATE CHANGE MITIGATION TECHNOLOGIES IN INFORMATION AND COMMUNICATION TECHNOLOGIES [ICT], I.E. INFORMATION AND COMMUNICATION TECHNOLOGIES AIMING AT THE REDUCTION OF THEIR OWN ENERGY USE
Y02E	REDUCTION OF GREENHOUSE GAS [GHG] EMISSIONS, RELATED TO ENERGY GENERATION, TRANSMISSION OR DISTRIBUTION
Y02P	CLIMATE CHANGE MITIGATION TECHNOLOGIES IN THE PRODUCTION OR PROCESSING OF GOODS
Y02T	CLIMATE CHANGE MITIGATION TECHNOLOGIES RELATED TO TRANSPORTATION
Y02W	CLIMATE CHANGE MITIGATION TECHNOLOGIES RELATED TO WASTEWATER TREATMENT OR WASTE MANAGEMENT

Source: The classification is based on CPC (Espacenet, 2022)

Table A1.2: ICB Industry Classification System

Industry	**Description**
Technology	Containts companies that are primarily engaged in the advancement of the information technology and electronics industries.
Telecommunications	Contains companies that own and operate telecommunication infrastructures to provide content delivery services
Health Care	Contains companies that manufacture health care equipment and supplies or that provide health care-related services such as lab services, in-home medical care and operate health care facilities.
Financials	Contains companies engaged in savings, loans, security investment and related activities such as financial data and information providers.
Real Estate	Contains companies engaged in real estate investment, development, and other real estate related services.
Consumer Discretionary	Contains companies that provide products and services directly to the consumers, and their purchasing habits are non-cyclical in nature (discretionary).
Consumer Staples	Contains companies that provide products and services directly to the consumers, and their purchasing habits are cyclical in nature (staples).
Industrials	Contains companies engaged in manufacturing and distribution of capital goods and provider of business support services.
Basic Materials	Contains companies that extract or process raw materials , and manufacturers of semi-finished goods such as chemicals, textile, paper, forest products and related packaging products.
Energy	Contains companies that engage in energy extraction, process, and production activities and produce related energy equipment.
Utilities	Contains companies that distributes electric, gas, and water.

Source: The classification is based on ICB Industry Classifiction (FTSE Russell, 2022)

A2 Implied Cost of Equity

Variables:

r_E = Easton's Implied Cost of Equity

r_{OJ} = Ohlson & Jüettner-Narouth Implied Cost of Equity

P_t = Stock Price at year t

EPS_{t+x} = Forecasted Earnings per Share in year t + x

DPS_{t+1} = Dividends per Share in year t + 1

LTG = Long Term Growth Rate

γ = The rate of expected continual earnings growth. In the model, this equals the risk-free rate less than 3%, with the 3% representing economy growth

Model 1: Easton (2004)

$$P_t = \frac{EPS_{t+2} + r_E \times DPS_{t+1} - EPS_{t+1}}{r_E^2} \tag{.1}$$

Model 2: Ohlson & Jüettner-Narouth (2005)

$$r_{OJ} = A + \sqrt{A^2 \frac{EPS_{t+1}}{P_t} \times (g_t - (\gamma - 1)} \tag{.2}$$

Where:

$$A = \frac{1}{2} \times ((\gamma - 1) + \frac{DPS_{t+1}}{P_t}) \tag{.3}$$

$$g_t = \frac{1}{2} \times (\frac{EPS_{t+2} - EPS_{t+1}}{EPS_{t+1}} + LTG) \tag{.4}$$

A3 Definition of Variables

Table A3.1: Variable Definitions and Sources

Variable	Definition	Source
Dependent Variables:		
COE	The Cost of Equity is the expected rate of return equity holders demand that the company pays out. Bloomberg calculates by Equation (1)	Bloomberg Terminal
Implied COE	Implied Cost of Equity estimated based on the research from (Easton, 2004) and (Ohlson & Juettner-Nauroth, 2005). Average of two models to reduce forecast bias.	Author's calculation based on data from DataStream
Equity Issue	Calculation based on (El Ghoul et al., 2017): $\Delta BookEquity + \Delta DeferredTaxes - \Delta Retainedearnings$	Author's calculation based on data from Refinitiv
Transition Risk	Calculation based on (Dijk et al., 2021): $\frac{Emission(CO_2) \times CO_2price(\frac{\$}{CO_2})}{Profits}$	Author's calculation based on data from Refinitiv and OurWorldData
Credit Risk	Calculation based on (Altman, 2000): $1.2 \times \frac{WorkingCapital}{TotalAssets} + 1.4 \times \frac{RetainedEarnings}{TotalAssets} + 3.3 \times \frac{EBIT}{TotalAssets} + 0.6 \times \frac{MarketCap}{TotalAssets} + 1 \times \frac{WorkingCapital}{TotalAssets}$	Author's calculation based on data from Refinitiv
Measure of Green Innovation:		
Green Citations $_{t-1}$	Natural Logarithm of the total number of green citations received on a patent from year t - 1	OECD
Green Patents $_{t-1}$	Natural Logarithm of the total number of green patents received in year t - 1	OECD
Green Share $_{t-1}$	$\frac{GreenPatents_{t-1}}{TotalPatents_{t-1}}$	Author's calculation based on data from OECD
Control Variables:		
Size	Natural Logarithm of the firms' total assets	Author's calculation based on data from Refinitiv
BTM	The ratio of book value divided by market capitalization	Author's calculation based on data from Refinitiv
Beta	Beta from Bloomberg, calculated as a regression of the weekly return on each stock's local market return over the last five years.	Bloomberg Terminal
Leverage	The ratio of debt value divided by the equity value	Author's calculation based on data from Refinitiv
Total Patents $_{t-1}$	Natural logarithm of the total number of patents in year t - 1	OECD
GDP	Natural Logarithm of the GDP per capita in the firm's country	OECD

A4 Model Specification

A4.1 Year- and Industry Fixed Effects

Figure A4.1: Cost of Equity over Time for Different Industries

Visually, we can argue that there exist a time-trend in our data. The reason for the development in cost of equity through the period, is explained by unobserved variables. Therefore, to take time-specific variation in our data into account, year-fixed effects are included in our model.

Furthermore, visually, we can also argue that figure A5.1 indicate industry-specific variation that is constant through the period. Industry fixed effects are important because it can effectively control for time-invariant characteristics of an industry. The control variables Beta, Size, BTM and Leverage will control for some of this variation, but there is likely to be variation explained by unobserved variables. Therefore, to take industry-specific variation in our data into account, industry-fixed effects are included in our model.

A5 Model Testing

In this section, we discuss whether the assumptions of our model is satisfied.

A5.1 Zero Conditional Mean

There are likely to be explanatory variables not included in the analysis. Including year- and industry fixed effects will reduce the omitted variable bias. We control for omitted variable bias by including several fixed effects, but there could still be omitted variables that explain differences in COE. It is important to have the zero conditional mean assumption in mind since it is difficult to test, but the consequence of a violation is that we cannot interpret the coefficients causally (Wooldridge, 2012).

A5.2 Heteroskedasticity

We have tested for heteroskedasticity using a Breusch-Pagan test and the test results in table A5.1 imply heteroskedasticity in every model. Furthermore, to allow for heteroskedasticity we cluster standard errors at firm level for all models.

Table A5.1: Breusch-Pagan Test for Heteroskedasticity

Model	Chi2	P-Value
Main Regression Model	429.34	0.000
Robustness: Green Patents	371.44	0.000
Robustness: Green Share	275.24	0.000
Robustness: Implied COE	376.82	0.000

A5.3 Autocorrelation

Autocorrelation in the model is tested by performing a Durbin Watson test. The test results displayed in table A5.2, imply that there is autocorrelation in our data. However, when we cluster standard errors as adressed above, we correct for firm-observations being correlated across years.

Table A5.2: Durbin-Watson Test for Autocorrelation

Model	P-Value
Main Regression Model	0.000
Robustness: Green Patents	0.000
Robustness: Green Share	0.000
Robustness: Implied COE	0.000

A5.4 Multicollinearity

Multicollinearity is tested for by our correlation matrix in section X, and calculating variance inflation indicators (VIF). The results for VIF are presented in the table A6.3. Despite high correlation between green innovation and total patents, the results indicate no violation of the multicollinearity assumption in the models. For the sake of space, a correlation matrix for the Investor base and Risk channel is not provided, but it does not suggest high correlation between variables.

Table A5.3: Variance Inflation Factor

	Main Regression	Green Patents	Green Share	Implied COE
Green Innovation	2.66	2.84	1.04	2.66
Size	2.36	2.37	2.41	2.47
Leverage	1.29	1.3	1.32	1.32
BTM	1.50	1.50	1.49	1.53
Beta	1.48	1.48	1.50	1.50
Total Patents	3.11	3.27	1.57	3.06
GDP	2.49	2.49	2.45	2.42
Mean VIF	2.52	2.35	1.61	2.47

A5.5 Normality

According to Wooldridge (2016), we can apply the central limit theorem to conclude for normal distribution if the sample is large enough. With more than 6000 observations, we perceive the number of observations to be satisfactory for this conclusion. To decide whether the variables should be log transformed, we consider if it simplifies the interpretation of the model and if it improves the normality of the model. For example, in the case of GDP, a unit increase will not explain much. For the measures of patent-variables it follows prior research to use natural logarithm.

Based on Q-Q plots, which is made to assess whether the residuals are normally distributed, we have log transformed the explanatory and some control variables to improve the validity of the model. The normality of the model suggest that the residuals are still not perfectly normally distributed, but it will have limited effect on the analyses (Wooldridge, 2012).

A5.6 Correcting for Outliers

We have observed extreme values for balance sheet data and to avoid bias caused by outliers in our analysis, we winsorize all balance sheet data by 1% and 99% percentiles. The effect can be seen in table A6.4

Table A5.4: Correcting for Outliers

	Before Winsorization	After Winsorization
	Mean	Mean
Size	23.49	25.5
Leverage	133.25	107.42
BTM	121.66	60.13

Balance sheet data used in regressing the arguments is also winsorized by 1% and 99% percentiles, but we do not report these.

When we correct for outliers, the goal is to correct for extreme outliers. Therefore, removing an outlier just for the sake of it could be a mistake. For example, the minimum value of the Bloomberg Cost of Equity is 3.05%, a healthcare company's cost of equity in 2014. The company has COE values ranging from 3% to 8%, and treating its lowest value as an "outlier" would be wrong. In contrast, the maximum cost of equity is 33.7% which is the cost of equity for a bank in 2010. Moreover, we do not remove "outliers" from the Bloomberg Cost of Equity because we do not believe any values to be extreme, and removing them would therefore be a mistake.

A6 Regression Tables

Table A6.1: Slack Resource Theory

	Dependent variable:
	GreenPatents
RoA	0.01
	(0.01)
Size	0.05*
	(0.02)
Leverage	-0.00**
	(0.00)
BTM	0.00
	(0.00)
Beta	0.24***
	(0.09)
TotalPatents	0.53***
	(0.03)
GDP	-0.09
	(0.13)
Industry Fixed Effects	Yes
Year Fixed Effects	Yes
Observations	6,517
R^2	0.65
Adjusted R^2	0.65
Note:	*p<0.1; **p<0.05; ***p<0.01