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Corruption and Green Innovation in Italian Firms

And The Role of Firm Size

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ABSTRACT

Italy is considered the most corrupt country in Europe. Meanwhile, the country ranks on the higher end with its green inventions. Corruption is assumed to impede green innovation, yet the effect has not been extensively researched on the firm level, especially for developed countries. This study aims to map the effect of corruption on green innovation for Italian firms, because research has shown the effect to be very specific to contextual factors. Two panel regressions with random effects are conducted. The second regression executes a moderation analysis to investigate if the effect differs for smaller firms. No significant effect was found. After running additional analyses to uncover a possible relationship, still no significant effect between corruption and green innovation was found. The analyses were constrained by the data, since the green innovation level in the sample was low. A sample with high green innovation levels is hard to find due to the nature of the concept. This study has contributed by providing information on an additional context alongside the existing research contexts. The specific factors this study deals with, have proven to eliminate the effect of corruption on green innovation. This provides firms with tools to assess the risk and negative consequences of corruption. Furthermore, it helps policymakers with additional information about what must be taken into consideration to encourage sustainable development.

Keywords: Corruption, Green Innovation, Sustainable Development, Italy

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CHAPTER 1 Introduction

In the western world more and more green innovations are introduced to the market. In the Netherlands green innovations are constantly being researched at, among others, the Wageningen University & Research and Technological University Delft. For example, in 2013 Boyan Slat established the NGO The Ocean Cleanup dedicated to cleaning the ocean from plastics. In 2019 he developed a device called the inceptor for this purpose.[1] Also, the first smog vacuum has been introduced in 2015 by the Dutch Daniel Roosengaarde, called The Smog Free Tower.[2] In other western countries the same surge can be seen. Beyond Meat, founded in 2009, is an American company that mimics the taste of meat through an innovative approach and sustainable alternatives.[3] Italy is no exception to the trend. In 2022, Italy was ranked eighth in the Eco-Leaders group of EU member states.[4] In addition, it ranked first in resource efficiency. However, its economy has lagged behind in multiple ways compared to its western companions: mostly due to stagnant productivity. There are big inequalities between regions: the more south the region, the lower the GDP (Fina et al., 2021). Italy is also considered the most corrupt country in the EU. And corruption has been shown to stunt economic growth (Gründler & Potrafke, 2019).

The effect of corruption on green innovations has been studied more frequently in the recent years. Wen et al. (2023) have found that corruption has a negative effect on green innovation by analysing multiple countries on their corruption score and national green innovation. The effect is caused by a reduction in green innovation demand and an increase in its opportunity costs, according to Quan et al. (2023). While for OECD countries corruption is negatively correlated with green innovation, for non-OECD countries this relationship seems to be positive (Zakari et al., 2022). Troisi et al. (2023) have investigated the situation in Italy. Here, sustainable development has proven to be reduced by corruption. Wu et al. (2022) covered the effect of anti-corruption on green innovation and discovered that a positive relationship between the two exists. In addition, they found that the effect is partially mediated by rent-seeking and is more pronounced for firms with strong political ties. Chen et al. (2022) examined the Chinese energy-intensive industries for the same effect. They found R&D investments from high-tech, state-owned enterprises (SOEs) in regions with more government intervention or weaker intellectual property protection were more distinguished after the anti-corruption campaign. Green innovation is desirable and pursued by governments. It positively impacts firm performance (Zhang et al., 2019), but this does mainly apply to SOEs in the Chinese sample.

Most research done either focusses on country level corruption and green innovation or on developing countries like China and Vietnam. While Italy has been included in these country level

[1] www.theoceancleanup.com
[2] www.studioroosegaarde.net/project/smog-free-tower
[3] www.beyondmeat.com
[4] www.green-business.ec.europa.eu/eco-innovation_en

studies, research on the firm level is scarce. The economies studied on a firm level are in a different economical state than western economies. Green innovation may be differently affected due to the contextual factors. The disparity in economical phase provides unlike environments. Apart from Troisi et al. (2023) the Italian economy has not been subject to empirical investigation with respect to this relationship. Since Italy is considered the most corrupt country of the EU, it is an interesting country to conduct this research. It has an history of corrupt leaders. However, in the recent years Italy's Corruption Index Score has increased from 42/100 in 2012 to 56/100 in 2023.[5] In addition, Italy is scoring well on the Eco Innovation Index. Hence, it seems anti-corruption goes with an increase in green development. To determine if Italy needs to focus on anti-corruption policies to boost its economic growth and green innovation, the effect of corruption needs to be defined. Therefore, this thesis aims to answer the following questions:

How does corruption affect green innovation in Italian firms? And is this effect different for smaller firms?

I will focus on data before the corona crisis in 2020. The data spans from 2012 to 2017 from Italian, non-financial firms, since the corruption data is available up to 2017 and some regional statistics from 2012. The independent variable is defined as number of green patents applied for. The data on patents will be extracted from the World Intellectual Property Organization (WIPO) and the green classification will be based on the IPC Green Inventory offered by WIPO. Firm data and characteristics will be retrieved from the Datastream database. Two panel regression analyses will be employed to conduct the analyses with and without the moderator with the dimensions set to firm and time. This way there will be controlled for firm-invariant and time-invariant effects. Corruption will be defined as the number of white-collar crimes in the corresponding region per 1000 habitants. This data is released by the Italian National Institute for Statistics (ISTAT) and Eurostat. Crimes with the classification "offences against the public administration by public officers" are counted as white-collar crimes. This ISTAT classification entails bribery, corruption, embezzlement, extortion and abuse, misuse or breach of public office duties. The moderator is defined as firm size. It will be measured by taking the natural logarithm of the total assets of the firm. The OECD (2020) has reported that the biggest motivation for companies to establish an anti-corruption compliance program is to protect its reputation. The internet plays an important role in a firms' reputation as information is readily accessible and scandals or positive events are reported with ease. Therefore, to test the relationship between corruption in Italy and green innovation, a two-stage least squares panel (2SLS) regression will be run with the instrumental variable (IV) of the percentage of individuals who regularly, meaning more than once a week, use the internet. Based on the Hausmann test either fixed or random effects will be added. There will be controlled for relevant firm characteristics and regional factors.

[5] www.transparency.org

I hypothesize that between corruption and green innovation in Italian firms a negative relationship exists. On the national level, it has been demonstrated that corruption in Italy stunts economic growth. In the context of constrained economic growth, green innovation will be impeded. When looking at specific firms, I expect to see the consequences extended to the individual firms. This effect has also frequently been proven for Chinese firms. Contextual differences are involved, but corruption has shown to be detrimental around the world. Therefore, I expect the coefficient of corruption to be significant and negative. This would correspond with the stagnant productivity Italy has been dealing with. For bigger firms, I expect the effect to be less pronounced. These firms hold more resources and economic power to overcome the negative effects of corruption. Smaller firms are more constrained by corruption. Their innovation is therefore expected to suffer more under corruption. I expect the negative effect of corruption to be stronger for smaller firms.

First, relevant literature and previous research are discussed in chapter 2. Chapter 3 describes the sample and variables. The method is clarified in chapter 4. In chapter 5, the regression results are presented including robustness of the models and a hypothesis evaluation. Concluding remarks as well as recommendations for future research can be found in chapter 6.

CHAPTER 2 Theoretical Framework

2.1 Green Innovation

Environmental issues plague the world and are not expected to be solved soon. The sea levels are rising, extreme weather is becoming more frequent and carbon dioxide emissions reached a record high. Governments and regulatory organisations are desperately looking for ways to counteract these developments. Green legislation and regulations are being implemented. Furthermore, the importance of and demand for green technology has grown exponentially. Green and sustainable development cannot arise without green innovation. Not only the market demand and regulations incentivize firms to invest in green R&D. The increase in prices of fossil fuels and the global economic growth have pushed firms to switch to other means (Eyraud et al., 2011). Due to its relevance and usefulness, green innovation is highly researched in the recent years. The most active scholars on this topic are situated in Europe, especially the Netherlands, Italy and Germany (Schiederig et al., 2012).

Green or eco-innovation is defined by the OECD (2008) as *"the development of products (goods and services), processes, marketing methods, organizational structure, and new or improved institutional arrangements which, intentionally or not, contribute to a reduction of environmental impact in comparison with alternative practices"*. Sustainable, ecological or green innovation are three denominations for the same concept and are usually interchangeable. Literature shows slightly different uses that ultimately come down to the same view. It refers to the development of environmentally friendly products and/or processes. This is mostly achieved through the usage of greener or fewer materials with the aim of reducing emissions, preventing pollution and reducing the consumption of raw materials, electricity and water (Gunasekaran & Spalanzani, 2012). The impact of a firm's activity on the environment is lowered. The firm will meet existing environmental regulations and additionally have a competitive advantage over its competitors, according to Chang (2011). Through Structural Equation Modelling (SEM) Chang explored the mediating role of green innovation in the relationship between environmental business ethics and competitive advantage. Green innovation is a differentiation strategy for firms, and they can use this to obtain a competitive advantage.

Green technology innovation has shown to bring more advantages to economies and firms rather than just environmental benefits. The double dividend stems from limiting the environmental burden and contributing to the modernization of the economy (Rennings et al., 2006). The foundation of a sustainable society is laid by balancing economic growth with environmental conservation (Sun et al. 2008). Innovation overall is associated with economic growth. More innovation in general is usually present alongside green innovation (Hasna et al., 2023). Weng et al. (2015) demonstrated, by administering a survey among Taiwanese manufacturing and service companies, that waste and cost reduction positively affect firm performance, socially and financially. When a firm pioneers in green innovation, it should enjoy a first mover advantage (Aguilera-Caracuel & Ortiz-de-Mandojana, 2013). Their green products can be set at a premium, while their brand reputation is improved (Chen, 2008).

Furthermore, new markets open up, and social, environmental and ethical issues are better incorporated in the decision-making. Yuan & Cao (2022) introduced the green dynamic capability and showed that corporate social responsibility within a firm promotes innovation overall, but also green innovation in particular. When firms possess strong green dynamic capabilities, it enhances the ability to utilize existing resources and knowledge to update and develop its green organizational capability to adapt to the dynamic market. Aguilera-Caracuel and Ortiz-de-Mandojana have found that firms with green innovation of a higher intensity have more competence to improve their financial performance. Contextual, like national, factors are important in the benefits a firm experiences.

2.2 Corruption

Corruption is a broad term that can be and is given various definitions. The definition determines what is modelled and measured. Using public authority for private gains is reflected in every definition. Improper behaviour as bribery, extortion, fraud and more is often subsumed under this term (Wedeman, 2004). Besides having various definitions, corruption is difficult to measure. Given its illegal nature the activities do not typically take place publicly. However, when observed, there is usually no discussion on whether particular behaviour connotes corruption. Corruption can be found in three kinds of relationships: grand corruption by political leaders, bureaucratic corruption by appointed bureaucrats to superiors or the public and legislative corruption by legislators (Jain, 2001). Just discretionary power does not constitute corruption. For example, in Singapore the government is very important, but it receives a low corruption score.[6] For the possibility of corruption discretionary power, economic rents and a low probability of detection must co-exist. Corruption seems to be more present in developing countries and bureaucratic governments. Corruption is not only a political, but also an economic problem.

Corruption has a negative effect on a country’s economy in multiple ways. A low GDP is associated with corruption (Graf Lambsdorff, 2006). In with a panel regression analysis of approximately 50 countries, Mo (2001) determined that the growth rate of the GDP also declines with the increase of corruption. This effect is largely caused by political instability. Other studies suggest positive effects of corruption. It seems heterogenous effects exist. D’Agostino et al. (2016) researched the manner in which corruption affects economic growth. With simulations, they highlighted the significant, indirect impact of corruption on military spending and government investment expenditure. These correlations resulted in, given their different output elasticities, heterogeneous effects on economic growth rates. Nonetheless, the general consensus remains that the overall effect of corruption is damaging. The weakness of central government enhances the negative effect of corruption on economic development (Scheifler & Vishny, 1993). Lower agencies and private agents can enforce more bribes. A country’s attractiveness to investors, both international and domestic is lowered, because the

[6] www.transparency.org

costs are higher. In addition, government expenditures are distorted. Secrecy is more valuable to the corrupt officials. High value projects might need to make room for less useful projects if they provide a better shield. It discourages valuable investments and growth. This results in significant welfare losses.

Corruption is persistent and remains a current, global issue. Anti-corruption is on most governments' agenda and multiple global efforts exist. The United Nations Convention Against Corruption (2004) is the largest global anti-corruption instrument that is legally binding. Furthermore, projects like the Global Anti-Corruption Consortium[7] and events like the OECD Global Anti-Corruption & Integrity Forum[8] and the International Anti-Corruption Conference[9] are organised to construct and implement a global approach.

2.3 Empirical Studies

The relationship between corruption and green innovation is a relatively new researched topic that has gained more popularity in the recent years. Corruption's effect on firms has been researched earlier. According to Sahakyan & Stiegert (2012), corruption is in some cases viewed as favourably by a firm after conducting a survey under around one hundred Armenian businesses. Larger firms with fewer competitors and older firms have a higher chance of perceiving corruption as favourable. They found that this probability doubled when switching from a competitive market to an oligopoly or monopoly. Colonnelli & Prem (2022) have shown that corruption makes it harder for new firms to enter a market. This indicates that encouraging competitiveness in the markets can serve as an anti-corruption tool. Wang & You (2012) found that the financial constraint of corruption might not apply to emerging markets. In that context corruption can enhance firm growth. It functions as a substitute for financial development. This means that one's influence grows when the other's influence weakens. However, in a developed market corruption does not have zero effect, but it deters firm growth. The results of Van Vu et al. (2018) demonstrate different impacts of several types of corruption on firms' financial performance in Vietnamese SMEs. Paying bribes for public services might increase the financial performance, while paying informal costs to secure licences and government contracts tends to negatively affect financial performance. Ambiguous effects exist due to firm characteristics and contextual factors, but most forms of corruption do have a negative effect on firm financial performance.

Innovation is an indicator of firm performance. During a difficult economic period, a firm must allocate its resources to other more urgent objectives. In a better period, a firm has excess funds and more opportunity to invest this in R&D and innovate. With four analytical approaches, including two probit models, an ordinary least squares (OLS) and a 2SLS, Bukari & Anaman (2021) have exhibited the detrimental effect of corruption on innovation. The likelihood of adopting innovation through certificates, patents and R&D is reduced. In lower-middle income countries and Africa this effect is

[7] https://gacc.occrp.org
[8] www.oecd.org/corruption-integrity/forum/home/
[9] https://iaccseries.org/

more intense. The cost of innovation for firms increases with corruption. Officials might ask for bribes when applying for patents or certificates. Larger firms can benefit by a reduction of the time between application and acquisition. Smaller firms will not be able to pay the bribe and will suffer under these conditions. However, in the case of patents officials have poor negotiation powers. A patent can always be applied for at the international office.

Corruption also seems to have negative effects on sustainability (Morse, 2006; Aidt, 2011). However, reliable and valid data on sustainability is hard to retrieve. Therefore, the exact size and scope of the effect has yet to be determined. In contrast, Troisi et al. (2023) found a favourable link between corruption and sustainability. Again, it seems dependent on contextual factors. Tawiah et al. (2024) looked at the effect on green growth in 123 countries through a System-Generalized Method of Moments (S-GMM). Their results show a negative relation between corruption and green growth, which indicates that corruption hinders the efficient use of natural assets in production. Corruption seems to always undermine sustainable development in developed countries (Fihma et al., 2023). Yet in developing countries, corruption can enhance sustainable development when the governance is weak. Frovola et al. (2019) have argued that corruption is the biggest factor hindering sustainability. Corruption is used by officials to control behaviour of firms including their ‘green’ behaviour. Moreover, it gives firms room to circumvent regulations and proceed with their operations less ‘green’ than obliged. Research on the link between corruption and sustainability is not exactly conclusive. The vagueness of sustainability might be the cause of this.

Green innovation is a better tool to look at the sustainable development within firms and the markets. In line with the research on innovation in general and sustainability, green innovation also suffers under corruption. When a firm allocates resources to relationship-investments like bribes, it is forced to take out resources from elsewhere (Quan et al., 2023). Green innovation will receive less investments and the innovation level declines. Chen et al. (2022) researched the Chinese energy-intensive industry with the use of the Difference-in-Differences method. They found a positive relationship between anti-corruption and R&D investments, indicating corruption is an obstacle to innovation. This effect was more pronounced in SOEs and in regions with more governmental intervention. While the signing of International Environmental Agreements diminishes this effect in the short term, it seems to worsen the effect in the long run (Wen et al., 2023). Zakari et al. (2023) showed that the effect of corruption on green innovation is dynamic and again depends on contextual factors. They conducted an analysis with S-GMM on a panel sample on a country level. In OECD countries the negative effect of corruption was shown. However, in non-OECD countries their research displayed a positive effect of corruption. They attributed this to the demand for green innovation as a factor contributing to a country’s economic growth. Firms will try to bypass regulations with bribes.

2.4 Corruption and Innovation: The Case of Italy

The discussed literature has shown that the relationship between corruption and green innovation is very specific and dynamic. Therefore, a conclusion that applies to any context is difficult to draw. Each paper has specified that its results highly depend on contextual factors. They can only conclude on the specific situation they have taken their sample from. Most of the studies are country level or have taken a sample of companies in developing countries, specifically China. However, China is very specific in its political and economic situation. In addition, little data is public and the data that is made public by China is not always reliable. Hence, those results might not be universally applicable. There is clear need for further research. Italy differs from China on the economic and political level. However, the urge for sustainable development is felt the same in Italy. The manufacturing industry is targeted by the Italian government (Embassy of Italy in the UK, 2020). Investments are made and the industry undergoes a transformation. Italy is on the top end of the world with its green inventions; 9.6% of all patents filed in Italy are green.[10] These patents can mostly be found in the categories alternative energy production, waste management, and energy conservation.

Italy is also considered one of the most corrupt countries in the Eurozone. The country has long been plagued by corruption. In the early 1990's a nationwide judicial investigation called *Mani Pulite* (= Clean Hands) was set up. Thousands of officials and businesspeople were prosecuted (Henneberger, 2002). The top two political parties, the Christian Democrats and the Italian Socialist Party, ceased to exist. It was believed that Italy was swiped clean of most corruption. However, these beliefs unfortunately have proved false. The two years an anti-corruption bill has languished in parliament before it was passed in 2014, is evidence of reluctance under Italy's national leaders. More scandals have arisen in later years. Vannuci (2009) argues that the legacy of *Mani Pulite* only consists of an escalation of tensions between political powers and the judiciary. The scandals are more concentrated in regional and local politics rather than at the national level as with *Mani Pulite* (Barber, 2012). The political corruption is still systemic, and it has spread after the clean-up in the 1990's, according to Vannuci. It lingers in the modern Italian society. However, after *Mani Pulite* national, anti-corruption efforts were largely set up. In 2009 The Italian National Anti-Corruption Authority was established as an independent regulatory body.[11] With regulatory and supervisory activities like confiscating documents, inspecting offices and direct intervention in public work contracts under investigation, they monitor public agencies for transparency, compliance and enforce anti-corruption guidelines. Through this new organization and new anti-corruption legislation, Italy is making efforts to deal with its active corruption.

Previously discussed literature has shown different effects of corruption on green innovation. In addition, it has been demonstrated that this effect is dependent on contextual factors. Where country

[10] www.wipo.int
[11] www.anticorruzzione.it

level studies have included Italy before, Troisi et al. (2023) are the first to have studied Italy on a firm level to my knowledge. With two SEM analyses they researched the relationship between corruption, innovation and sustainability. Their results uncovered multiple relationships. Innovation and corruption have a positive relationship with sustainability when it is measured by sustainable industrialization and production-related indicators. The correlation remains positive, when sustainability is measured by employment and work-related indicators. However, the relationship with corruption turns negative. Troisi et al. have also found that innovation in its turn, affects corruption. When high levels of innovation are present, firms have no incentive to give bribes due to efficiency. Competitiveness in the market will push firms to achieve these levels. Corruption would then become useless. Some innovations however might encourage corruption. According to Budhwar et al. (2022), digitalized technologies can lead to corrupt practices due to lack of knowledge under the users.

Again, ambiguous relations exist between corruption and innovations, but the overall correlation appears negative. This has been proven in firm level studies for other countries, especially developed countries. Moreover, the country level studies have proven that corruption stunts the economic growth, which will stunt green innovation. While in some developing or low-income countries corruption might be favourable to firms, in developed markets it has been shown to have a negative impact. On a firm level this relationship will be carried through. Therefore, the following testable hypothesis for my empirical analysis arises:

Hypothesis 1. Corruption has a negative effect on firms' green innovation measured by patents.

In line with previous literature, I expect this effect to be less pronounced in larger firms, because they view corruption as more favourable. Paunov (2016) found that the negative effects of corruption on the ownership of quality certificates are stronger for smaller firms. He did not find that effect for patent ownership. However, Paunov researched emerging and developing countries and defined its variables different from this study. Smaller firms are hit harder by the negative effects of corruption. Bigger firms have more resources to achieve its goals through alternatives and circumvent the corruption. The negative effects of corruption can be overcome with resources, which smaller firms usually lack. With these resources, firms can also pay for the 'benefits' of corruption. Larger firms have the ability to compensate or avoid the negative effects. This ability is missing in smaller firms. Therefore, smaller firms and their green innovation will suffer more under corruption as they cannot afford the benefits or overcome the drawbacks. The second, testable hypothesis is as follows:

Hypothesis 2. The negative effect of corruption on green innovation is stronger for smaller firms.

CHAPTER 3 Data

3.1 Sample

The most frequent researched countries are in Asia. Especially China is often explored. Italy provides a very different context, because it is advanced in its economic phase and has a different political structure. There is a public database of population statistics, which makes the data easily accessible. The research will also be more reliable due to better verifying abilities. I have collected panel data on 118 Italian, non-financial firms listed on the Borsa Italiana. This data was retrieved from Datastream. The end of the data period has been set before 2020 to exclude the corona pandemic and its economic consequences. The data of the corruption proxy is published by the government for up to 2017. The regional statistics are available from 2012. The data analysis will therefore cover this period. The dataset consists of firms in multiple industries with the exception of those operating in finance and insurance. The firms in finance and insurance tend to diverge in their investment behaviour. On average the firms have a net income of 77 million euros per year, a market capitalization of 1.45 billion euros and total assets with a book value of 5.39 billion euros.

3.2 Variables

3.2.1 Dependent Variable

Green innovation is measured in green patents in line with the theory. This provides concise, public data and it focusses on outputs of the inventive process (Griliches, 1990; Haščič and Migotto, 2015). The vast majority of inventions with economic relevance have been patented (Dernis and Guellec, 2001). Other used measurements like R&D expenditure lie further from the desired observation. Firms might invest significant amounts to increase their green image to investors, yet the output is not observed. The generation of green innovations is not guaranteed. The share of green innovations in all innovations is also not captured by this measurement. Patent data provides extensive information about the nature of the invention, inventors and applicant. The application date is used to date the patents, because there is usually a lot of delay between the application and acquisition of a patent. This data was retrieved from the Patentscope offered by the WIPO. Every patent receives an International Patent Classification (IPC) from WIPO. In addition, they developed the IPC Green Inventory containing a list of every green classification. Each patent from each firm was looked at and its classification was checked for green IPCs. The count of all green patents per year constitutes the dependent variable and is defined as *GI*.

3.2.2 Independent Variable

Different measures for corruption are used in the existing literature. More data is available on a country level, e.g. the Corruption Perception Index. However, it does not suit this analysis as the variable in question does not vary for firms. In addition, many measurements are subjective, which makes it less reliable and more difficult to interpret. In this thesis, corruption is measured in offences against the public administration by public officers per region, as done by previous authors (Del Monte & Papagni, 2001; Corrado & Rosetti, 2018). The numbers have been converted to per 1000 inhabitants to take the size of the regions into account. Crimes of peculation, malversation, bribery, corruption and violation of the duties and abuse of office are included. It entails the number of people convicted by the final judgement. This measurement is directly observable and objective. However, due to the illegal nature of these activities the real number is probably higher. This measure presents the lower bound of corruption. The effect of corruption therefore might be underestimated. This data is provided by the ISTAT up to the year of 2017. The regions were linked to the location of the headquarters of the firms. Thus, corruption will take on the value of the corresponding region of a firms' headquarter location. The variable is defined as *Corr*.

3.2.3 Moderator

It has been proven firm size plays a role in the effect of corruption. Paunov (2016) found that smaller firms are hit harder by corruption. The biggest cause is the lack of resources to pay bribes or overcome corruption cause these differences. In addition, larger firms enjoy a larger network. This network will help to pass the negative effects of corruption. Where small firms will struggle to deal with corruption and simultaneously keep innovating, larger firms have sufficient employees and funds to do both. To analyse the moderating effect of firm size on the effect, the size variable is computed. Following the literature (Tang et al., 2020; Chen et al., 2022), it is measured by taking the natural logarithm of the total assets. These numbers are obtained from Datastream and the variable is defined as *Size.*

3.2.4 Control Variables

The control variables were chosen based on the presented literature to exclude alternative explanations. To control for heterogeneity between regions and its impact on local corruption, region-specific variables are added, following Quan et al. (2023). Italy struggles with big regional, economic differences. Therefore, it is important to control for this heterogeneity. Additionally, some firm-specific control variables are used.

Population density *(Popd)*: Population density in persons per square kilometre represents the physical connectivity people have within their region. According to Roche (2020), physical connectivity has a positive impact on innovation. Knowledge exchange is organized more efficiently and more easily available in these areas. Through knowledge exchange different fields and industries are connected, which sparks problem solving and innovative solutions. The data was obtained from Eurostat.

Regional GPD per capita *(GDP)*: To account for the economic differences, it is important to control for the difference in regional GDP. The data was retrieved from Eurostat. The data consists of regional GDP per inhabitant in Purchasing Power Standards (PPS: an artificial currency). By taking the natural logarithm, the effect of GDP growth is included. I expect the variable to have a positive effect on green innovation, since it is associated with a good economic environment and conjuncture. When GDP rises, more resources become available and these can be invested in innovation.

Unemployment rate *(Unemp)*: Unemployment can have a negative impact on innovation, according to Majewska & Rawińska (2018). They found that the growth rate of innovation declined as unemployment rose, which in turn increased unemployment further. In order to account for the aforementioned effect, the unemployment rate per region is controlled for. This data is retrieved from Eurostat.

Leverage *(Lev)*: There is controlled for leverage, because it might affect innovation performance (Gu et al. 2016; Zhou et al., 2020). Due to interest payments a firm will have less means to invest in R&D and the firm will also have less debt-financing options. The variable was computed as follows: $Leverage = \frac{Total\ Liabilities}{Total\ Assets}$. These numbers were retrieved from Datastream.

Return on assets *(ROA)*: This is a proxy for the profitability of a firm (Chang et al., 2019). It shows whether a firm is doing well or not and whether it has capacity to invest in R&D. Firms use return on assets to optimize asset investment. More profitable firms have been shown to have higher levels of innovation (Tang et al., 2021). With data from Datastream, the variable is computed as follows: $Return\ on\ Assets = \frac{Income\ before\ Extraordinary\ Items}{Total\ Assets}$.

Tobin's Q *(TQ)*: We control for investment opportunity by adding Tobin's Q, as often done in studies (Xu & Yano, 2017; Chen et al., 2022). Tobin's Q represents the ratio between a firm's market value and the replacement cost of its total assets. A high value indicates a firm has good investment prospects and hints at growth potential. Green investments improve the prospects of a firm, and the investment opportunity will be increased. The variable is computed as follows: $Tobin's\ Q = \frac{Market\ Capitalization}{Total\ Assets}$. These numbers were obtained from Datastream. The natural logarithm is taken of the variable to mitigate outliers.

3.3 Descriptive Statistics

Table 1 shows the descriptive statistics of all variables. A significant proportion of the sampled companies have no green patents, which accounts for the low mean of green innovation. The population density variable shows that on average about 333 people live per square kilometre in the regions. The average GDP is much higher than the global average, but this is expected for a western country. The unemployment rate mean lies closer to the minimum than the maximum, meaning that a few regions rise above the rest. The firms in the sample have a low return on assets on average, since a ROA above 0.05 is considered good and excellent above 0.20. About the financing structure, statistics show that the average company has slightly more liabilities than assets. The mean of Tobin's Q (4.149) is relatively high due to outliers that can be discovered by the maximum value (1016.686). After deleting five outliers of Tobin's Q (>100), the mean falls to 0.938. This means that the average company is valued by the market close to its true value. To mitigate the outliers, the natural logarithm is taken from Tobin's Q.

Table 1

Descriptive Statistics.

Variable	Mean	Std Dev	Min	Max
GI	0.401	2.066	0	27
Corr	0.127	0.095	0.024	0.379
Popd (*100/m^2)	3.335	1.153	0.686	4.392
Ln(GDP)	10.381	0.164	9.735	10.551
Unemp (%)	8.89	2.87	6.30	21.70
Int (%)	65.89	6.62	40.36	76.31
ROA	-0.010	0.187	-1.294	3.132
Lev	0.670	0.305	0.074	4.26
Ln(TQ)	-1.107	1.916	-12.377	6.924
Size	19.972	2.080	13.270	25.870

Table 2 shows the correlation between all independent variables. Except for the unemployment rate and GDP, none of the variables are highly correlated (>= 0.8) with each other. However, the correlation between corruption and the unemployment rate and GDP and the population density are elevated. The high correlation between *Unemp* and *GDP* can cause multicollinearity problems. Multicollinearity can cause coefficient estimators to be less accurate.

Table 2

Correlation Matrix of the Independent Variables.

	Corr	*Popd*	*Ln(GDP)*	*Unemp*	*ROA*	*Lev*	*Ln(TQ)*	*Size*
Corr	1							
Popd	-0.1550	1						
Ln(GDP)	-0.3059	0.5237	1					
Unemp	0.5865	-0.1981	-0.8524	1				
ROA	-0.1270	-0.0785	-0.0281	-0.0974	1			
Lev	0.0242	-0.1009	-0.0254	0.1009	-0.3383	1		
Ln(TQ)	-0.0689	0.1177	-0.0993	-0.1762	0.2277	-0.3171	1	
Size	0.1009	0.0084	0.0556	-0.0229	0.204	-0.1245	-0.1349	1

To check the Variance Inflation Factor (VIF) of each variable, for each year a separate regression is run. The VIF helps assess the severity of possible multicollinearity between variables. It shows the contribution of the variable to the standard error in the regression. Table 3 shows the VIF for each variable in each year. As expected, *GDP* and *Unemp* show high estimates that increase by the year. Furthermore, the VIF estimates for *Popd* score close to the threshold of high correlation (>= 5) and above it in the year 2016. The VIF estimates for *Corr* approaches the threshold in the years 2016 and 2017. The year 2016 has the highest mean of the VIF estimators.

Table 3

VIF Estimates for the OLS Regression including All Variables.

Variable	2012	2013	2014	2015	2016	2017
Corr	3.00	2.97	3.09	3.52	4.72	4.87
Popd	4.09	2.97	2.79	3.75	5.50	3.53
Ln(GDP)	12.82	13.97	13.85	15.01	28.57	26.62
Unemp	11.67	14.07	14.71	16.78	31.23	32.35
ROA	1.27	1.40	1.28	1.63	1.17	1.81
Lev	1.32	1.82	1.72	1.63	1.11	1.75
Ln(TQ)	1.44	1.47	1.50	1.15	1.21	1.18
Mean	5.09	5.52	5.56	6.21	10.50	10.30

To further investigate which variable should be dropped, two regressions are run: one excluding *GDP* and on excluding *Unemp*, again for each year separately. Table 4 shows the VIF estimates of the regression excluding *Unemp*. No estimates have a value above the threshold. The highest mean is observed in 2017.

Table 4

VIF Estimates for the OLS Regression excluding Unemp.

Variable	2012	2013	2014	2015	2016	2017
Corr	1.03	1.09	1.12	1.28	1.24	1.51
Popd	1.50	1.44	1.47	1.52	1.50	1.50
Ln(GDP)	1.47	1.44	1.52	1.63	1.71	2.02
ROA	1.26	1.39	1.28	1.62	1.16	1.78
Lev	1.28	1.80	1.70	1.58	1.09	1.69
Ln(TQ)	1.43	1.46	1.50	1.12	1.21	1.17
Mean	1.33	1.44	1.43	1.46	1.32	1.61

Table 5 shows the VIF estimates of the regression excluding *GDP*. Again, no estimates cross the threshold. The year 2017 still produces the highest mean. Tables 4 and 5 do not show big differences in values. Therefore, the model will be tested with both variable combinations.

Table 5

VIF Estimates for the OLS Regression excluding GDP.

Variable	2012	2013	2014	2015	2016	2017
Corr	1.31	1.42	1.53	1.86	1.79	2.36
Popd	1.04	1.09	1.11	1.16	1.09	1.11
Unemp	1.34	1.45	1.62	1.83	1.87	2.46
ROA	1.26	1.40	1.28	1.62	1.16	1.80
Lev	1.29	1.80	1.69	1.60	1.10	1.70
Ln(TQ)	1.43	1.46	1.50	1.14	1.09	1.18
Mean	1.28	1.44	1.46	1.53	1.37	1.77

CHAPTER 4 Method

The data has a clear panel structure with the dimensions firm and time. Accordingly, a panel regression is used for this analysis. The use of random or fixed effects enables the accounting of firm- and time-invariant characteristics. After conducting the Hausman test with the p-value above 0.05, the random effects estimator proved consistent. Therefore, random effects are included in the regression. This way systemic differences in time and between firms are controlled for. After categorizing the first ten firms separately and the remaining together, the mean standard errors were analysed for these categories (Table 6). Since the mean is not zero for all categories and the variance is not constant, the standard errors are firm-clustered to account for heteroskedasticity and autocorrelation. This is appropriate seeing the sample is not clustered (Abadie et al., 2023). Then, OLS regressions with random effects and firm-clustered errors are conducted to test my hypotheses. The regression to test my first hypothesis will take on the form of Eq. 1. The regression to test the second hypothesis will take on the form of Eq. 2.

$$GI_{i,t} = \alpha + \beta_1 Corr + \beta_j \omega_j + \varepsilon_{i,t} \tag{1}$$

$$GI_{i,t} = \alpha + \beta_1 Corr + \beta_2 Size + \beta_3 CorrSize + \beta_j \omega_j + \varepsilon_{i,t} \tag{2}$$

In these equations ω represents all the control variables. Because of the multicollinearity issues with *GDP* and *Unemp*, the model will be tested with *GDP* and *Unemp* separately. The model with the highest predictive power (R^2) will be chosen and used for the remaining analyses.

Table 6

Mean Standard Errors per Firm.

Category Name	Mean	Standard Deviation
A2A SpA	-0.015	0.416
Acea SpA	-0.039	0.026
Acinque SpA	-0.026	0.021
Aeffe SpA	-0.023	0.041
Alerion Clean Power SpA	-0.025	0.029
Amplifon SpA	-0.022	0.020
Arnoldo Mondadori Editore SpA	-0.026	0.030
Ascopiave SpA	-0.007	0.052
Autostrade Meridionali SpA	-0.018	0.104
B&C Speakers SpA	-0.014	0.088
Other	0.002	1.054
Total	0.000	1.009

The sample is relatively small containing just over one hundred Italian firms. The average green patents per year are low (0.401). It shows not all firms have a green innovation. Therefore, uncovering a relationship may turn out more difficult. Not all firms actively invest in green R&D. This might be due to lack of resources, incentive or knowledge. Sustainability is still a newly explored area. Firms have few examples to go off on and might find it difficult how and where to begin improving their operations. Then, there are also firms that do invest in green R&D but simply have not found a functioning innovation. The signal can be weak due to these limitations of the data. Extra regressions will be run to amplify the signal and uncover a possible relationship. First, OLS regressions will be conducted for each year separately to analyse any issues with a specific year. Secondly, the green patents will be added up for each firm and the average over six years will be taken from the other variables. A new OLS regression will be run with the aggregated green innovation as dependent variable and the averaged variables as independent variables. Lastly, a dummy variable will be created for green innovation. The variable will take on the value 1 if the firm has acquired at least one green patent in six years and 0 otherwise. A logistic regression, as this is general approach with a dummy, dependent variable, will be conducted with the dummy variable as dependent variable and the averaged variables as independent variables.

Endogeneity will arise when the independent variable, *Corr*, is correlated with the regression's error term. Endogeneity will cause the OLS estimators to be biased, so the causal interpretation of coefficients might be compromised. These problems can emerge due to omitted variables, reverse causality or measurement errors. While control variables are included to reduce the possibility of omitted variables, it is impossible to rule out this possibility completely. The reverse causal relation is not often discussed in literature. Troisi et al. (2023) did find an effect of innovation in general on corruption. High innovation levels can decrease or increase the demand for corruption. Therefore, a possibility of a reverse causal relation exists. Lastly, measurement errors are always a hazard. However, considering every patent and IPC is checked manually, the probability of measurement errors is enlarged. For the possibility of omitted variables, reverse causality and measurement errors, an IV will be employed.

The IV must satisfy the relevance and exclusion conditions. It must be correlated with corruption, and it cannot be directly correlated with green innovation or the error term. The percentage of individuals who regularly, meaning more than once a week, use the internet (*Int*), was used. This variable was retrieved from Eurostat. It has been shown that internet access reduces corruption perception (Garcia-Murillo, 2014). Additionally, social media usage weakens corruption (Jha & Sarangi, 2017). The internet has a great influence on the reputation of a firm, because through its channels information is quickly spread. Reputation is the biggest motivation for firms to establish an anti-corruption compliance program (OECD, 2020). Furthermore, individuals can easily look up corruption information and enlarge awareness. Internet-driven transparency is increased, which lowers corruption activity. Considering competitiveness under the firms, it is not feasible they will share their innovation knowledge with each other before acquiring the patent. Besides, the firms are located within a reasonable distance which minimizes the potential impact of the internet on knowledge sharing. It is not likely internet usage will affect green innovation directly. Therefore, the conditions of an IV are satisfied. With

Int, a Two-Stage Least Squares Regression (2SLS) will be conducted. This addresses the endogeneity issues and ensures consistent estimation of coefficients. In the first stage the relevance condition will be verified. In the second stage, the exogenous part of corruption is isolated and can be properly interpreted.

CHAPTER 5 Results & Discussion

5.1 Panel Regression

Table 7 shows three models. The first model does not incorporate any control variables. The coefficient is positive, but not significant. In model 2 control variables on the regional level are added. The coefficient of corruption has decreased. This signals that the observed effect in model 1 was overestimated and partially due to the influence of the control variables. However, no coefficients are significant. Model 3 contains only firm level control variables. The coefficient of corruption has increased slightly compared to model 1, but the values are close together. Still no estimates are significant, which means no significant effect is observed in the model 1, 2 and 3. Since R^2 also increased, it indicates the firm level controls account for variance that is not relevant to corruption. Because in both model 2 and 3 R^2 increased, all controls are used for further analysis.

Table 7

OLS Regression Results of Corruption on Green Innovation with Model 1 including No, Model 2 including Regional and Model 3 including Firm Level Control Variables.

Variable	Model (1)	Model (2)	Model (3)
Corr	0.883	0.186	0.902
	(1.276)	(0.981)	(1.273)
Popd		-0.042	
		(0.212)	
Ln(GDP)		1.686	
		(2.026)	
Unemp		7.939	
		(8.874)	
ROA			0.142
			(097)
Lev			0.061
			(0.068)
Ln(TQ)			-0.268
			(0.030)
Constant	0.289	-17.687	0.218
	(0.228)	(21.102)	(0.239)
Observations	708	708	708
Groups	118	118	118
R^2	0.0004	0.0027	0.0018

Note: Clustered standard errors between brackets; random effects included.

Since the correlation matrix and VIF estimates revealed high correlation between the regional GDP and unemployment rate, the model is tested with these variables separately. Table 8 shows the two models, where model 4 excludes *Unemp* and model 5 excludes *GDP*. While both models have a low R^2, the values are higher compared to model 2 and 3 indicating the usefulness of including both regional and firm level controls. Model 4 presents the highest R^2. This suggests model 4 has a higher predictive power; the variance of green innovation is better explained by this model. Therefore, this model will be chosen to conduct additional analyses with. However, it is noted that both R^2s are low, and the difference is small. In addition, no variables are significant in both models. Model 4 tests the first hypotheses. The coefficient of corruption is positive in both models, but no significant effect is found. This is not consistent with the first hypothesis.

Table 8

OLS Regression Results of Corruption on Green Innovation with Variable Selection. Model 4 excludes *Unemp* and Model 5 excludes *GDP*.

Variable	Model (4)	Model (5)
Corr	0.961	0.9638
	(1.221)	(1.312)
Popd	0.015	0.061
	(0.150)	(0.102)
ROA	0.148	0.142
	(0.101)	(0.099)
Lev	0.067	0.056
	(0.081)	(0.070)
Ln(TQ)	-0.033	-0.026
	(0.034)	(0.030)
Ln(GDP)	0.560	
	(0.776)	
Unemp		-0.059
		(1.633)
Constant	-5.661	0.016
	(7.755)	(0.346)
Observations	708	708
Groups	118	118
R^2	0.0064	0.0040

Note: Clustered standard errors between brackets; random effects included.

5.2 Moderation Analysis

The model excluding the unemployment rate is used for the moderation analysis. Table 9 shows the regression results after adding firm size as moderator. The second hypothesis is tested by this model. The R^2 has increased, which suggests firm size does add to the predictive power of the model. Table 11 (see appendix B) shows the marginal effect of corruption for constant values of firm size. The effect is the most positive for *Size* = 15 and decreases with an increase in firm Size. The estimates for *Size* = 23 and 25 are negative. Figure 1 also shows that the slope is decreasing. This points at a more positive effect of corruption for smaller firms and more negative for larger firms. This is partially consistent with the first hypothesis. Since the coefficient of model 4 is positive, Table 11 does suggest a stronger effect for smaller firms, albeit positive rather than negative. However, the model does not display any significant variables. After the first regression, insignificance of the coefficients of corruption and the interaction term is expected. When no significant relationship exists between corruption and green innovation, the effect cannot differ for small and large firms. The results show firm size also does not have a significant effect on green innovation. Green innovation seems unrelated to both variables. These results are not in accordance with the second hypothesis.

Table 9

OLS Regression Results of Corruption on Green Innovation for the Moderation Analysis with Firm Size as Moderator.

Variables	Model (6)
Corr	5.658
	(16.725)
Size	0.312
	(0.272)
Interaction Term (*Corr*Size*)	-0.253
	(0.882)
Popd	0.042
	(0.150)
Ln(GDP)	0.283
	(0.794)
ROA	-0.019
	(0.115)
Lev	0.056
	(0.096)
Ln(TQ)	0.023
	(0.047)
Constant	-9.004
	(7.105)
Observations	708
Groups	118
R^2	0.1158

Note: Clustered standard errors between brackets; random effects included.

5.3 Amplifying the Effect

First, each year is separately analysed to check for distortions in a specific year that contributes to the insignificance of the model. The regressions in Table 12 (appendix C) do not display any significant estimates. The year 2014 has the highest R^2 and the year 2016 and 2017 the lowest, but the differences are minimal. It indicates that not a specific year is problematic and the (in)significance of the model will not be improved by omitting one year. The coefficient of corruption is the most positive in 2015 and negative only in 2013.

Due to the small sample and little green innovation, the signal might be weak. Consequently, it will not show quickly in the panel regressions analyses. To uncover any existing relationship, two more regressions are conducted. The averaged independent variables are regressed on aggregated green innovation. Table 13 (appendix C) shows the estimates. Again, no significant variables arise. Next, the averaged independent variables are regressed on the dummy for green innovation in a logistic model. The results are displayed in Table 14 (appendix C). Still no significant relationship can be discovered between green innovation and any of the independent variables. It does note the average ROA becomes significant in model 9, which can be a sign of a significant effect of ROA on green innovation.

5.4 Endogeneity

To address possible endogeneity issues, an IV, frequent internet usage, is applied. Model 7 contains the results of the 2SLS regression without moderator and model 8 contains the results of the 2SLS regression with moderator. In the first stage, the relevance condition is verified. Internet usage is significant in both model 7 and 8, which indicates it is correlated with corruption. The relevance condition is fulfilled. Population density in model 7 and firm size, the interaction term and GDP in model 8 are also significant. This hints at correlation between population density, firm size and GDP and corruption, although these variables do not show a high correlation in Table 2 and 5. The fitted values of corruption are used in the second stage and regressed on green innovation. The second stage of both models show no significant coefficient estimators. Like demonstrated by the results, accounting for endogeneity problems does not improve the model.

Table 10

2SLS Regression Results of Corruption on Green Innovation using Frequent Internet Usage as IV. Model 8 includes the Moderator Firm Size.

Variables	Model (7)		Model (8)	
	First Stage	Second Stage	First Stage	Second Stage
Corr		5.604		38.699
		(9.034)		(100.796)
Size			-0.008**	0.587
			(0.001)	(0.734)
Interaction Term			0.049**	-1.874
(*Corr*Size*)			(0.001)	(4.884)
Popd	-0.023**	-0.049	0.000	0.048
	(0.005)	(0.337)	(0.001)	(0.145)
Ln(GDP)	-0.032	-0.154	-0.009**	0.298
	(0.027)	(0.757)	(0.004)	(0.798)
ROA	-0.002	0.128	-0.005	0.131
	(0.002)	(0.093)	(0.004)	(0.565)
Lev	0.009*	0.047	0.001	0.033
	(0.004)	(0.076)	(0.003)	(0.108)
Ln(TQ)	-0.002	-0.023	0.000	0.021
	(0.001)	(0.031)	(0.000)	(0.054)
IV (*Int*)	0.166**		0.014**	
	(0.043)		(0.004)	
Constant	0.419	1.402	0.245**	-14.699
	(0.263)	(6.858)	(0.038)	(22.375)
Observations	708	708	708	708
Groups		118		118
R^2		0.0003		0.0871

Note: Clustered standard errors between brackets; random effects included; *p<0.05, **p<0.01.

5.5 Hypothesis Evaluation

Two hypotheses were put forward in chapter 2. The first states: *"Corruption has a negative effect on firms' green innovation measured by patents."* This hypothesis was tested by a panel regression in model 4. The relationship presented is positive. However, the findings do not reveal a significant effect of corruption on green innovation. After manipulating the data, the results did not improve. A significant relationship remained absent. This is not in line with the hypothesis or the discussed literature. The country level studies find a negative effect of corruption in OECD countries (Zakari et al., 2022) or across the globe (Wen et al., 2023). In Zakari et al.'s full sample, including OECD and non-OECD countries a positive relationship was observed. Since Italy is an OECD country, a negative effect was expected. Troisi et al. (2023) did find a positive effect for Italy when sustainability was measured by sustainable industrialization and production-related indicators, like patents. However, no studies observed no effect of corruption on green innovation. The results of this study may diverge due to contextual factors. These factors play a big part in the established effect as evidenced by different outcomes in the discussed literature. Italy is more developed than most frequent researched countries in the firm level studies.

The second hypothesis that was tested reads as follows: *"The negative effect of corruption on green innovation is stronger for smaller firms."* A moderation analysis was conducted to test this hypothesis. The results of model 6 suggest a stronger effect for smaller firms, as the coefficient is more positive for a smaller firm size and the coefficient in model 4 was too positive. This is partially consistent with the second hypothesis, as the effect appears positive instead of negative. Nonetheless, no significant effect was observed in this model. This is in line with the results from the first hypothesis. Since no relationship exists between corruption and green innovation, it cannot differ between small and large firms. Again, this is not in line with the discussed literature. It has been established by Paunov (2016) smaller firms are hit harder by corruption. For innovation this applies mostly to the acquisition of quality certificates. The same relationship has not yet been identified with regard to the acquisition of patents, either within this study or in previous ones. Contextual factors and the nature of patents may be responsible. Patents can also be applied for at the international office, allowing firms to circumvent corruption at the national office and negate the effect of corruption.

CHAPTER 6 Conclusion

6.1 Concluding Remarks

The relevance and importance of green innovation is undenied across the globe. Especially the western countries have been investing in these projects. To stimulate sustainable development, countries need to tackle the obstructions slowing down the innovation. There is little literature on the subject, but corruption has shown to be detrimental. Although some studies found a positive effect in specific contexts, most established a negative relationship between corruption and green innovation. The various results prove the relationship depends on contextual factors. Little firm level studies exist for western countries, where green innovation activity is high. Due to the dependency on the context, it is important to analyse these countries also. Therefore, this thesis studies Italian firms for the effect of corruption on green innovation. The research questions this study aims to answer, read as follows: *"How does corruption affect green innovation in Italian firms? And is this effect different for smaller firms?"*

To conduct the analyses, panel data on 118 Italian firms listed on Borsa Italiana was obtained. Green innovation was defined by the number of green, by IPC, patents a firm applied for between 2012 and 2017. Corruption was gathered on the regional level. It was defined as the number of white-collar crimes per 1000 inhabitants, which are classified as "offences against the public administration by public officers". In addition, firm characteristics and controls on the regional level were included. Panel regressions, a moderation analysis and 2SLS regressions were conducted on this sample. Firm size was used as moderator to analyse the differentiation in the relationship between corruption and green innovation for smaller firms. To solve possible endogeneity problems, frequent internet usage was used as IV in the 2SLS regression.

The results did not find a significant effect of corruption on green innovation for the sample. The coefficient of corruption was positive in most models, suggesting a positive relationship with green innovation. However, none of the models presented a significant coefficient. The R^2 of all models was remarkably low. This indicates the variance in green innovation is not well explained by the models. The moderation analysis also did not provide a significant effect, which was expected after the first models. The results did indicate a stronger effect (more positive) for smaller firms when compared with the previous models, but again no significant estimates were discovered. After attempts to magnify a possible relation by manipulating the data, still no significant effect was found. Accounting for endogeneity issues did not improve the model either. Therefore, the irrefutable conclusion of this study is that no effect of corruption on green innovation exists in the sample of these 118 Italian firms.

These results provide new insights in the complex relationship between corruption and green innovation. There is minimal knowledge on the mechanism that works between the two, since it is a newly researched subject, as evidenced by the lack of early articles. Therefore, much is still to be discovered. The dependency on contextual factors has been established, which highlights the importance of research on different countries. Most firm level studies focus on countries in Asia. This thesis can be relevant to the academia, because it discusses a developed country on the firm level. The country level studies did include such countries. However, research on the firm level provides a better look at the actors in these activities. It may provide firms with tools to assess the risk and negative consequences of corruption. The absence of an effect in the results implies firms and their green innovation do not suffer under corruption. They should not allocate their sources to anti-corruption for this reason. It would be more efficient to allocate them elsewhere. Furthermore, the information can help policymakers with finding focus areas to improve sustainable development. Corruption should not be their main concern in establishing such policy. It is evident anti-corruption will stay on the governmental agenda for different reasons.

6.2 Future Research

This study contains several limitations that must be considered. The sample is smaller than similar studies. Since green innovation is a fairly new initiative and hard to attain for firms, it is hard to obtain a sample with high green innovation levels. The onset of sustainable innovation is often met with numerous challenges in the majority of industries. In addition, skilled workers are scarce, since education is not yet tailored to the transition. The number of green patents in the sample could be increased by including more firms or extending the time period. Green innovation is also often more concentrated in specific industries. Researching these industries separately could give more clarification on the mechanism between corruption and green innovation.

Different measurements of corruption and green innovation may also provide new insights. Both subjects are hard to define and even harder to measure. The illegal nature of corruption makes it difficult to report. The number of convictions, used as proxy in this study, will always be the lower bound. Using predicted levels of corruption could come closer to the true value. A possible effect will be uncovered quicker with more information. Green innovation also knows multiple measurements. With the use of patents, green classification is the biggest hurdle. Although the IPC Green Inventory is provided, some patents do not have an IPC and the classifications are not frequently updated. Some studies have used the patent text to classify it. Usually, several words related to sustainability are chosen to select the patents. However, words can be used in various ways. The risk of missing green patents and including ones that are not green is present. While green patents are most commonly used, other proxies exist. By analyzing how proxies alter the definition of green innovation, the understanding of the relation with corruption can be increased. And with the usage of other proxies, this possible relation can differ and be more easily observed.

Lastly, future research could focus more on the mechanism of corruption and understanding what factors play a role in the relation with green innovation. While diverse contexts have already been the subject of research, investigation into more contexts could add to the academic horizon. However, mapping the mechanism could provide more insight in the effect for multiple contexts. With more insight in the mechanism, a framework could be set up that can be adjusted for specific contextual factors instead of having to examine all context separately. The fundamental objective is to compose a generally applicable structure, where the effects of corruption can be predicted and analyzed for all countries.

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APPENDIX A Researched Firms

Below a list of the researched firms can be found. The list contains 118 Italian firms publicly traded on the Borsa Italiana based in Milan. They all run as the legal form of corporation *Societa per Azioni* (=Public Limited Corporation). All companies have their headquarters located in Italy.

A2A SpA
Acea SpA
Acinque SpA
Aeffe SpA
Alerion Clean Power SpA
algoWatt SpA
Amplifon SpA
Arnoldo Mondadori Editore SpA
Ascopiave SpA
Autostrade Meridionali SpA
B&C Speakers SpA
Basic Net SpA
Bastogi SpA
Beewize SpA
Bestbe Holding SpA
Bialetti Industrie SpA
Biesse SpA
Bioera SpA
Brembo NV
Brioschi Sviluppo Immobiliare SpA
Buzzi SpA
Cairo Communication SpA
Caleffi SpA
Caltagirone Editore SpA
Caltagirone SpA
Cembre SpA
Cementir Holding NV
Centrale del Latte d'Italia SpA
Centro HL Distribuzione SpA
CIR SpA - Compagnie Industriali Riunite
Class Editori SpA
Compagnia Immobiliare Azionaria SpA
CSP International Fashion Group SpA
Danieli & C Officine Meccaniche SpA
Datalogic SpA
Davide Campari Milano NV
De' Longhi SpA
DiaSorin SpA
Digital Bros SpA
Edison SpA
EEMS Italia SpA
El En SpA
Elica SpA
Emak SpA
Enel SpA
Enervit SpA
Eni SpA
ERG SpA
Esprinet SpA
Eukedos SpA
Eurotech SpA
Exprivia SpA
Fidia SpA
Fiera Milano SpA
FNM SpA
Gabetti Property Solutions SpA
Gas Plus SpA
Gefran SpA
Geox SpA
Greenthesis SpA
Hera SpA
I Grandi Viaggi SpA

Il Sole 24 Ore SpA
Immobiliare Grande Distribuzione SIIQ SpA
Immsi SpA
Interpump Group SpA
IRCE SpA
Iren SpA
Italmobiliare SpA
Juventus FC SpA
KME Group SpA
Landi Renzo SpA
Leonardo SpA
Maire Tecnimont SpA
Marr SpA
MetExtra Group SpA
MFE-MEDIAFOREUROPE NV
Mondo TV SpA
Monrif SpA
Netweek SpA
Newron Pharmaceuticals SpA
Next Re SIIQ SpA
OLIDATA SpA
Piaggio & C SpA
Pininfarina SpA
Piquadro SpA
PLC SpA
Poligrafici Printing SpA
Prysmian SpA
Recordati Industria Chimica e Farmaceutica SpA
Reply SpA
Risanamento SpA
Rizzoli Corriere della Sera Mediagroup SpA
Sabaf SpA
Saes Getters SpA
Safilo Group SpA
Saipem SpA
Saras SpA
Seri Industrial SpA
Servizi Italia SpA
Snam SpA
Softlab SpA
Sogefi SpA
SOL SpA
SS Lazio SpA
Telecom Italia SpA
Terna Rete Elettrica Nazionale SpA
Tesmec SpA
Tessellis SpA
Tod's SpA
Toscana Aeroporti SpA
TXT e solutions SpA
Valsoia SpA
Vianini SpA
Vincenzo Zucchi SpA
Visibilia Editore SpA
Webuild SpA
Zignago Vetro SpA

APPENDIX B Additional Results from the Moderation Analysis

This appendix provides additional information on the interaction in the moderation analysis. These results give a better insight in the effect of the moderator. A visual representation of the interaction is also provided to increase the understanding.

Table 11 shows the marginal effects of corruption on green innovation keeping the moderator, firm size, constant at different levels. The coefficient gets less positive when the size increases. The coefficient is negative from *Size* =23. These changes are visualized in Figure 1. The slope flattens until *Size* =21 and can be seen turning down from *Size* =23. It indicates the effect of corruption on green innovation is more positive for smaller firms.

Table 11

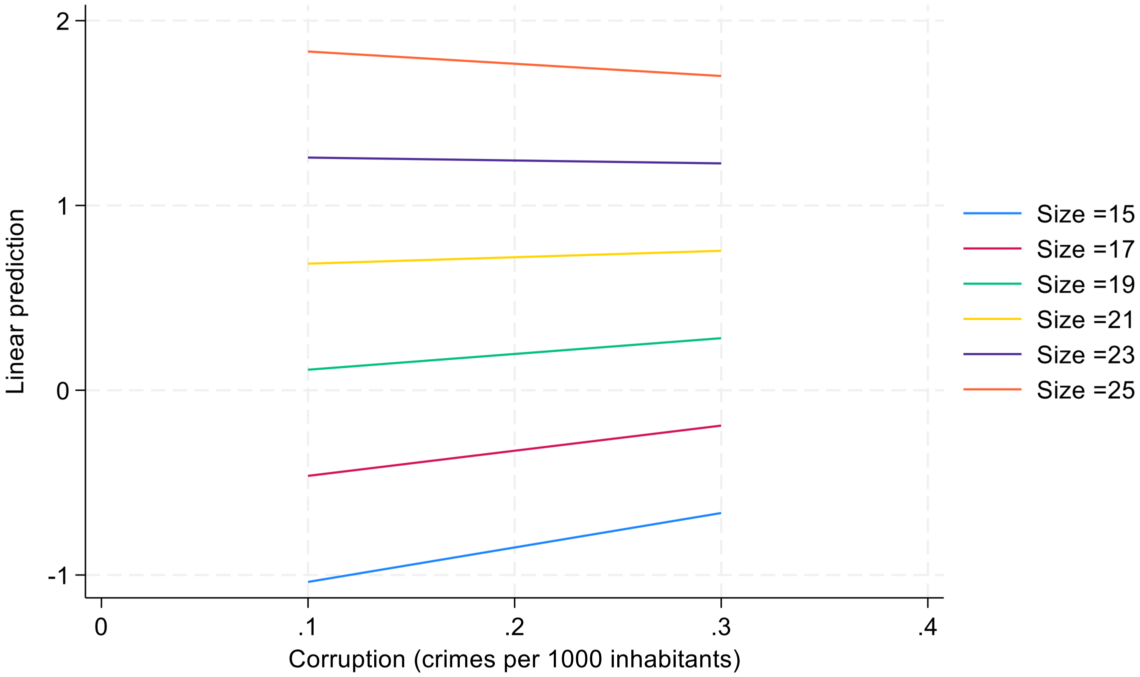
The Average Marginal Effects of Corruption at Constant Values of Firm Size.

Constant Value	*Corr*
Size =15	1.865
	(3.553)
Size =17	1.359
	(1.860)
Size =19	0.854
	(0.719)
Size =21	0.348
	(1.949)
Size =23	-0.158
	(3.647)
Size =25	-0.663
	(5.388)
Observations	708

Note: Clustered standard errors between brackets.

Figure 1

The Predicted Margins of Corruption at Constant Values of Firm Size.



APPENDIX C Additional Regression Results

This appendix provides the results of the extra regressions that are run to uncover distortions and/or a possible relationship between corruption and green innovation. The signal can be weak due to small variation in green innovation. Therefore, the data is manipulated to amplify the possible effect.

Table 12 contains the results of the OLS regressions run for each year apart from each other. It shows the coefficient of corruption positive for all the years except 2013. The coefficient in the year 2015 provides the biggest value. The model for 2014 seems to have the highest predictive power. However, no variables are significant in any of the years indicating the problem does not lie within a specific year of the panel data.

Table 12

OLS Regression Results of Corruption on Green Innovation for Each Year Separately.

Variable	2012	2013	2014	2015	2016	2017
Corr	0.498	-0.239	0.526	2.002	1.303	1.451
	(1.361)	(1.133)	(1.417)	(2.220)	(2.166)	(1.944)
Popd	0.177	0.190	0.076	-0.073	-0.042	-0.095
	(0.150)	(0.189)	(0.055)	(0.208)	(0.214)	(0.178)
Ln(GDP)	0.498	0.664	0.489	1.107	1.135	1.054
	(0.268)	(0.356)	(0.392)	(0.604)	(0.614)	(0.725)
ROA	1.846	1.069	0.951	0.662	0.180	0.264
	(1.173)	(0.750)	(0.668)	(0.541)	(0.233)	(0.460)
Lev	-0.105	-0.713	-0.477	0.108	0.077	-0.036
	(0.328)	(0.592)	(0.472)	(0.389)	(0.288)	(0.226)
Ln(TQ)	-0.019	-0.064	-0.120	-0.108	-0.098	-0.077
	(0.055)	(0.061)	(0.123)	(0.121)	(0.100)	(0.55)
Constant	-5.400	-6.610	-4.919	-11.172	-11.468	-10.565
	(2.909)	(3.621)	(3.947)	(6.131)	(6.476)	(7.683)
Observations	118	118	118	118	118	118
R^2	0.0195	0.0180	0.0513	0.0156	0.0113	0.0113

Note: Clustered standard errors between brackets; *p<0.05.

The dependent variable, green innovation, is aggregated to increase the variation. This will enhance a weak signal. The results are displayed in Table 13. The coefficient has increased compared to the previous models, but still no significant effect is discovered in model 9.

Table 13

OLS Regression Results of Average Corruption on Green Innovation Aggregated over 6 Years.

Variable	Model (9)
Average Corruption	6.312
	(9.789)
Average Population Density	0.272
	(0.859)
Average ln(GDP)	4.444
	(2.351)
Average ROA	6.553
	(3.600)
Average Leverage	-1.928
	(2.662)
Average ln(Tobin's Q)	-0.557
	(0.570)
Constant	-44.692
	(24.461)
Observations	118
R^2	0.0151

Note: Clustered standard errors between brackets.

Lastly, the data is manipulated by transforming green innovation into a dummy variable. The results of the logistic regression with the dummy variable as dependent variable are presented by model 10 in Table 14. The coefficient of average corruption implies the probability of having a green patent in these 6 years increases with 62.7% for a 1 unit increase in the average corruption. However, this model also does not uncover a significant relationship between corruption and green innovation. It does note the average ROA is significant in this model, indicating a possible correlation with green innovation.

Table 14

Regression Results of the Logit Model of Average Corruption on the Green Innovation Dummy.

Variable	Model (10)
Average Corruption	0.627
	(3.278)
Average Population Density	0.222
	(0.229)
Average GDP	0.992
	(1.373)
Average ROA	6.742*
	(2.777)
Average Leverage	-1.344
	(1.049)
Average Tobin's Q	-0.259
	(0.142)
Constant	-12.096
	(14.607)
Observations	118
R^2	0.0623
χ^2	8.54
Log likelihood	-53.227

Note: Clustered standard errors between brackets; *p<0.05.