London School of Economics and Political Science

ESSAYS IN CLIMATE FINANCE

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Declaration

I certify that the thesis I have presented for examination for the Ph.D. degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

I declare that the thesis consists of 27,112 words excluding appendices.

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Abstract

This thesis explores the role of finance in facilitating a transition to a greener economy and the impact of climate risks on markets and corporations.

The first chapter examines how firms respond to transition risks by focusing on the EU Emissions Trading System (EU ETS) and its impacts. Leveraging the EU ETS's inclusion criteria and subsequent regulatory tightening, a fuzzy regression discontinuity and a difference-in-differences analysis reveal two types of spillovers: emission spillovers, as firms shift emissions across supply chains, and technology spillovers, as firms increase their technological activities following stricter regulations.

The second chapter investigates the pricing of building insurance, a critical market for climate adaptation. It studies the price dispersion of building insurance policies on a UK price comparison website. Using real property data and fictitious customer profiles, the study obtained quoted annual price data from the website and documented that, even after controlling for differences in policy features, individual customers still face considerable price dispersion, and the degree of dispersion varies significantly across customers. This dispersion is partially explained by customers' preferences for certain providers. Further analysis indicates that variations of risk pricing strategies across providers and the use of randomized pricing strategies also contribute to the observed price dispersion patterns.

The third chapter assesses whether corporate green bonds could improve the greenness of the economy. A simple theoretical framework shows that one potential channel for green bonds to make the world greener is through their use by financially constrained firms as a commitment device. However, empirical evidence shows that current issuers are typically less financially constrained and already greener than non-issuers. This suggests that green bonds may not significantly influence firms' environmental behaviors under current market conditions.

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Chapter 1

The Ripple Effects of Carbon Regulation: Insights from the EU ETS

Abstract

This paper examines the impacts of the EU Emissions Trading System (EU ETS). Using a fuzzy regression discontinuity (RD) design that leverages the unique inclusion criteria of the EU ETS, this study finds that while regulated firms significantly reduced their Scope 1 emission intensity, there was a concurrent more than twofold increase in Scope 2 emissions, suggesting potential emission spillover through supply chains. This finding is supported by a decrease in the percentage of European suppliers, who are typically under stricter environmental regulations. Further investigation reveals that as the regulation became more stringent, firms began seeking technological solutions for compliance, evidenced by increased technological connections, particularly in their role as licensees. Contrary to expectations, regulated firms experienced increases in revenues and profits compared to their unregulated counterparts. This outcome may be attributed to the oversupply of allowances in the early phases and the ability of regulated firms to pass higher costs onto customers.

1.1 Introduction

With escalating global attention on combating climate change, the interest in implementing carbon pricing[1] to mitigate greenhouse gas (GHG) emissions is on the rise. As reported by World Bank (2023), as of April 2023, there are 73 carbon taxes or emission trading systems (ETSs) in operation, covering 23% of global carbon emissions, with ETSs alone responsible for over 18% of these emissions. Given the increasing adoption and substantial reach of carbon ETSs, it is imperative to gain an in-depth understanding of the effectiveness of these trading systems in addressing the negative externalities of carbon emissions. Motivated by this need, this paper aims to shed light on this question by studying the European Union Emissions Trading System (EU ETS). As the world's first major carbon market, the EU ETS serves as a pivotal model for global cap-and-trade systems, making its study critical for understanding the broader impacts of such policies.

Since its launch in 2005, the EU ETS has been pivotal in reducing emissions from regulated entities by 37%, while maintaining the financial stability of these firms (Dechezleprêtre et al., 2023), as per the European Union's report[2]. However, for a complete evaluation of such environmental policies, it is essential to consider not just the direct effects on regulated entities but also the potential indirect effects or spillovers. Two types of spillovers should be considered when it comes to such environmental regulation and thus are the focus of this paper: The first primary spillover concern is pollution spillover, in this case, carbon leakage[3], which occurs when firms may shift emissions to avoid expensive emission reduction measures. Another crucial spillover is innovation, where regulatory pressure leads to the

[1]According to Timilsina (2022), carbon pricing can be broadly categorized into three types: fiscal or pricing policies, regulatory policies, and direct public investment. Pricing policies include instruments such as carbon taxes, emission trading, and subsidies.

[2]See: https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/what-eu-ets_en and https://www.oecd.org/environment/eu-emissions-trading-system-does-not-hurt-firms-profitability.htm/

[3]The EU characterizes carbon leakage as the risk of businesses in highly competitive sectors relocating outside the EU to countries with more lenient greenhouse gas emission standards. Source: https://ec.europa.eu/commission/presscorner/detail/en/IP_09_1338

development of low-carbon technologies that could also benefit unregulated firms. This study, focusing on the period between 2005 and 2020, combines detailed data from various sources to investigate these spillovers. The emissions data from S&P Trucost include both the direct (Scope 1) and indirect (Scope 2) emissions of firms, enabling an assessment of potential carbon leakage across firms' supply chains. Meanwhile, the supply chain data from FactSet Revere, which includes information on firms' technological connections, aids in examining innovation spillovers.

Identifying the impacts of the EU ETS presents a challenge due to the non-random nature of its implementation. Firms covered by the EU ETS are likely to differ inherently from those not covered. To address this issue, this paper employs a fuzzy regression discontinuity (RD) design, leveraging a unique characteristic of the EU ETS where only plants with input capacities above a certain threshold are subject to the regulation. However, the absence of detailed data on plants' input capacities makes a sharp RD design based on the exact regulatory threshold infeasible. To circumvent this limitation, the study instead employs the output capacity data from the WEPP database as the running variable. While output capacity is not the same as the regulated input capacity, the two are interconnected through plant efficiency, defined as the ratio of output to input capacity. Assuming the plant efficiency distribution meets specific criteria, the probability of a plant being regulated based on its output capacity should exhibit a noticeable jump around the the mode of the efficiency distribution. This observed jump in the data represents a left-shifted version of the actual input capacity threshold, effectively serving as an alternative measure for the true regulatory threshold. A graph depicting the regulation probability against output capacity for eligible plants confirms a significant discontinuity, establishing the basis for the fuzzy-RD analysis.

The fuzzy-RD analysis reveals that while EU ETS-regulated firms significantly lowered their Scope 1 emission intensity (measured as $tCO2e/US\$mnRevenues$), there is a more than twofold increase in their Scope 2 emissions, implying a possible shift of emissions across supply chains. Upon examining the geographic distribution of the regulated firms' supply chains, I find that the number of European customers has significantly increased. In contrast, there appears to be a decrease in the number of European suppliers, although this decrease is not statistically significant. Notably, there is a marked reduction in the percentage of European suppliers, particularly in the early stages of the EU ETS, with decreases of 68.8% in Phase 1 and 36.6% in Phase 2. From a financial perspective, the EU ETS seems to have had a minimal effect on the overall profitability of firms, despite recording some increase in revenue. Additionally, the study explores technological spillovers but identifies no significant effects in this area.

As a robustness check, I further leveraged the different levels of increase in regulatory stringency for regulated firms in 2013 as a natural experiment to conduct a difference-in-differences (DID) analysis on the same outcome variables. Almost all results are consistent with those found in the fuzzy RD analysis. However, contrasting with the fuzzy RD results, where no significant impacts of regulation were found on firms' technological links, here an increase in regulatory stringency has led to a notable increase in both the number of technological links and the turnover of these technological relationships. Detailed examination shows that while firms under stricter regulation are more actively licensing patents and technology from other companies, they licensed their own patents and technology to fewer companies. Furthermore, firms facing a larger increase in regulatory stringency also increased their research collaboration in the first year of the regulation tightening. This pattern indicates that stricter regulation may foster more active technological exchanges, potentially leading to broader innovation spillovers as firms cannot entirely internalize the effects of the technology diffusion in the technology market (Arqué-Castells and Spulber, 2022). Besides the differences in the results for firms' technological links, the DID results confirm that regulation leads to higher revenue for regulated firms and also reveals that firms facing tighter regulatory stringency increased their net income.

Overall, the findings of this paper suggest that while the EU ETS has contributed to a decrease in GHG emissions among regulated firms, part of this reduction may be counterbalanced by leakage through supply chains. The rise in non-European suppliers aligns with the notion of carbon leakage. Financially, the regulation does not seem to negatively affect regulated firms. On the contrary, the revenues of regulated firms increased, and their net incomes also rose after the tightening of the regulation. These results are surprising, as purchasing emission allowances is akin to paying a tax, which should financially burden firms under stricter regulations. One explanation is that allowance banking since 2008 and the oversupply from the 2008 financial crisis meant tighter regulation did not immediately harm financial outcomes. Furthermore, since many regulated firms are large firms with market power, the demand of their customers is relatively inelastic. Thus, regulated firms can pass any increased costs to their customers without sacrificing sales, leading to higher revenue. While this does not fully explain the positive impacts of tighter regulation on net income, it suggests that increased regulatory stringency does not hurt firms' bottom line in the short run. As for impacts on firms' technological networks, it seems the EU ETS only has significant impacts on technological relationships once they are binding. The tighter regulation increased dynamics in the technology market, creating more opportunities for technology and innovation to spillover through interactions among firms. However, as this study does not examine other channels of innovation spillovers, a more comprehensive understanding of the EU ETS's overall impact on firms' innovation and related spillovers requires further research.

This paper contributes primarily to the existing body of research on the impacts of the EU ETS. While previous studies have explored various effects of the EU ETS, including emissions, economic performance, and innovation, this study distinguishes itself in two primary aspects. Firstly, many existing studies lack robust identification strategies to address endogeneity issues arising from the non-random nature of the policy. Initial evaluations (e.g., Ellerman and Buchner, 2007, 2008; Anderson and Di Maria, 2011; Bayer and Aklin, 2020) primarily relied on sector-level data and trend extrapolation to construct counterfactuals. Subsequent research shifted to more granular data, utilizing firm-level (e.g., Calel and Dechezleprêtre, 2016; Calligaris et al., 2018) or combined firm and plant-level data (e.g., Petrick and Wagner, 2014; Dechezleprêtre et al., 2023), employing matched difference-in-differences methods. This was largely due to the unavailability of specific plant capacity data. To my knowledge, this paper is the first to overcome this limitation by exploiting the unique inclusion criteria of the EU ETS to identify its impact on firms. This approach offers a novel method for non-experimental analysis by leveraging policy design, paving the way for future studies. Secondly, while most research on the EU ETS focuses primarily on direct impacts on regulated firms, there is limited exploration of its spillover effects, with a particular scarcity of evidence beyond carbon leakage. Moreover, the existing results have been mixed: Naegele and Zaklan (2019) found no evidence of carbon leakage using sector-level trade flow data, and Dechezleprêtre et al. (2022) observed no significant geographical shift in emissions within multinational companies. Conversely, studies by D'Arcangelo and Galeotti (2022) and Böning et al. (2023) suggest some degree of carbon leakage. This paper, by conducting an in-depth analysis, extends the understanding of the EU ETS's broader impacts, including both direct effects and spillovers, thus contributing a more nuanced perspective to the literature.

This research also contributes to the extensive body of work examining the static and dynamic effects of environmental policies on businesses[4]. It closely relates to studies focusing on the impacts of various ETSs, as explored in research by Liu et al. (2022); Bai and Ru (2022); Shi and Wang (2022); Cui et al. (2023). Additionally, this paper contributes to a broad strand of studies examining the implications of different carbon pricing policies. For instance, the work of Aghion et al. (2016) investigates the role of carbon tax in driving technological changes. This study also adds to the literature on spillover effects of environmental policies, both within firms (as seen in Bartram et al., 2022) and across firms (as discussed

[4]According to Gillingham and Stock (2018), static cost estimates typically focus on the immediate consequences of environmental policies, while dynamic costs take into account a broader range of impacts, including indirect effects and the adjustments businesses make over time in response to these policies.

by Dasgupta et al., 2023). Furthermore, it contributes to the burgeoning field analyzing how climate actions are transmitted across firms' supply chains(e.g., Dai et al., 2021; HomRoy and Rauf, 2023), a topic of growing importance.

The rest of the paper is structured as follows. Section 1.2 provides a detailed introduction to the EU ETS, particularly its inclusion rules. Section 1.3 introduces the datasets used and explains the data cleaning process. Section 1.4 outlines the empirical strategy, while Section 1.5 presents the empirical results. Finally, Section 1.6 offers conclusions.

1.2 Institutional Background

1.2.1 Overview of the EU ETS

The EU Emissions Trading System (EU ETS), initiated in 2005, is a *cap and trade* system that sets limits on greenhouse gas (GHG) emissions from over 10,000 stationary installations[5] and aircraft operators within the EU, covering around 40% of the EU's emissions. The cap determines the total number of tradeable allowances, each permitting the emission of one tonne of CO_2 equivalent (tCO2e), thereby facilitating a cost-effective way of reducing GHG emissions.

The EU ETS has progressed through various phases, with the ongoing Phase 4 covering 2021-2030. This paper, however, concentrates on the first three phases. Figure A.1.1 in Appendix A.1 details the evolution of the coverage of the EU ETS. In each phase, both the emission caps and the free allocation of allowances are determined by legislation. Phase 1 (2005-2007) set caps based on historical emissions data, allocating nearly all allowances for free. This approach led to

[5]The term "installation" is defined as: "a stationary technical unit where one or more activities listed in Annex I are carried out and any other directly associated activities which have a technical connection with the activities carried out on that site and which could have an effect on emissions and pollution" (*see DIRECTIVE 2003/87/EC Article 3(e)*). While technically an installation is not exactly equivalent to a physical plant, it serves as a reasonable proxy in the context of this paper.

an oversupply and a price collapse by 2007 (as shown in Figure 1.1), as banking of allowances was not permitted until 2008. Phase 2 (2008-2012) saw a 6.5% reduction in the cap compared to 2005 and a slight decrease in free allocation to about 90%. A pivotal change occurred in Phase 3 (2013-2020), decreasing the cap annually by 1.74% for stationary installations and transitioning to auctioning as the primary method for allocating allowances, with 57% auctioned and the remainder allocated for free based on benchmarks[6]. Notably, the reduction in free allowances varies with sectors. While most electricity providers receive no free allowances anymore, installations in other sectors receive free allowances based on the emissions from the most efficient installations in the same product segment. Compliance within the EU ETS is enforced annually. Regulated entities are required to report their emissions by the end of March and to surrender an adequate number of allowances by April 30th each year. Non-compliance incurs penalties, initially €40/tCO2e in Phase 1 and increased to €100/tCO2e in Phase 2, rising with inflation from 2013.

Figure 1.1: EU Carbon Emissions Allowances Prices

Note: The figure shows the historical trends in EU carbon emissions allowance prices (EUR/allowance) from early 2005 to the end of 2023. Red vertical lines represent the start of the second, third, and fourth phases of the EU ETS, respectively.The green horizontal line represents the social cost of carbon (SCC) for the year 2015, estimated by Nordhaus (2017). The estimated value is \$31 per ton of CO_2 in 2010 US\$. (Source: https://tradingeconomics.com)

[6]Benchmarks were developed for each product, using the average GHG emissions efficiency of the top 10% installations producing that product, based on 2007-2008 data.

The effectiveness of the EU ETS in reducing GHG emissions has been a subject of debate. Figure 1.2 shows a decline in average verified GHG emissions for all stationary installations during the first three phases of the EU ETS. However, attributing this trend solely to the EU ETS is contentious, particularly as the carbon price necessary to limit global temperature rise to below $1.5C^\circ$ by 2100, as suggested by scholars, is significantly higher than the allowance prices in the initial phases of the EU ETS[7]. Nonetheless, the EU ETS may still motivate firms to lower their GHG emissions, even with the sub-optimal pricing in its initial phases, especially if there is an expectation of more stringent regulations in the future. Indeed, several studies (e.g., Dechezleprêtre et al., 2023; Bayer and Aklin, 2020; Petrick and Wagner, 2014) using plant-level data and matched or synthetic control methods have provided evidence indicating that, despite low allowance prices, the EU ETS has contributed to a reduction in GHG emissions.

1.2.2 The Scope of EU ETS

This subsection explains the scope of the EU ETS, a critical element for the empirical design of this study. While the EU ETS covers both stationary installations and aircraft operators, the focus here is on the former. An installation falls under EU ETS regulation based on the activities it conducts, which may not align with standard industrial classifications like NACE. Regulation is triggered if an installation exceeds the capacity thresholds for activities listed in Annex I of the EU ETS Directive. Table A.1.1 in Appendix A.1 displays the regulated activities and their thresholds for stationary installations from the EU ETS's inception in 2005, while Table A.1.2 lists additional activities added in 2011. These thresholds are categorized as either production capacity thresholds or total rated

[7] The estimated social cost of carbon (SCC) varies greatly with models and scenarios assumed in the model. The UK Government Economic Service (GES) recommended an illustrative estimate for the SCC of £70/tonne of carbon (tC), within a range of £35 to £140/tC in 2002. While the average SCC estimates from the U.S. government range from $4.7 to 35.1$ per tonne of CO_2 in 2007. However, the values from the U.S. government were calculated along a business-as-usual emissions path, not a socially optimal one (See: https://www.elibrary.imf.org/display/book/9781616353933/ch04.xml). The general consensus is that most carbon prices in reality are too low.

thermal input (RTI)[8] thresholds. While production capacity thresholds align more closely with industrial classifications, reflecting an installation's production output, RTI is applicable to combustion[9] activities across various NACE categories. For example, a hospital with its combustion units exceeding 20MWt falls under EU ETS regulation. For the purpose of this study, however, I only focus on installations belonging to private business sectors. It's notable that some installations engage in both combustion activities and other activities with thresholds defined by production capacity. These installations become subject to EU ETS regulation if any of these regulated activities exceed their respective threshold limits.

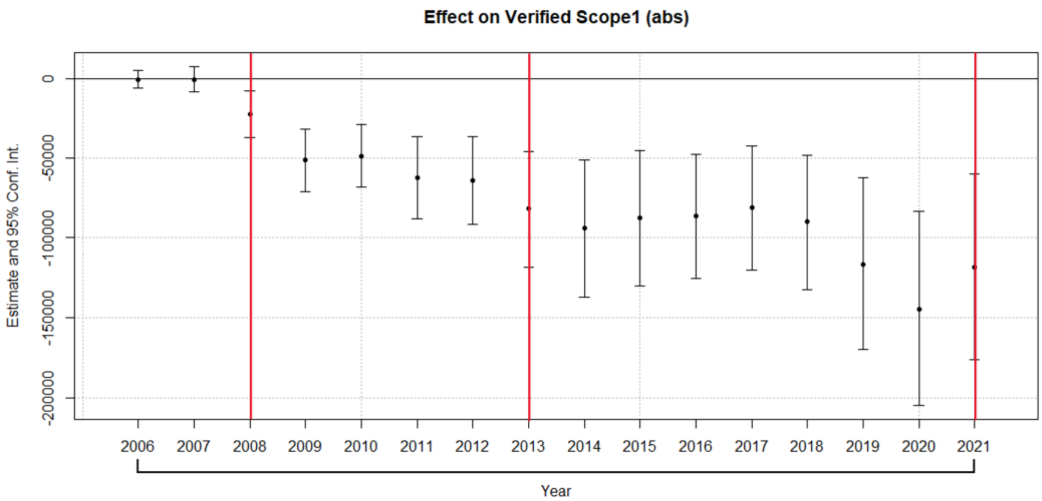


Figure 1.2: Verified Emissions for EU ETS Installations by Year

Note: The figure plots the annual average of verified greenhouse gas emissions (GHG) in tCO2e for all stationary installations covered by the EU ETS, adjusted relative to the 2005 average. This visualization is created using data from the European Union Transaction Log (EUTL). For each installation, the annual average relative GHG emissions are calculated, factoring in country, activity, and firm fixed effects. The vertical lines around each data point denote the 95% confidence interval. The three red vertical lines represent the start of the second, third and fourth phase of the EU ETS, respectively.

It's important to note that the EU ETS regulation for stationary installations is based on their capacity (or installed capacity) rather than actual usage. The

[8] *The rated thermal input (RTI) is the rate at which fuel can be burned at the maximum continuous capacity of the appliance multiplied by the calorific value of the fuel, expressed as megawatts thermal (MWt).* (Definition from: Scottish Environment Protection Agency (SEPA) - IED-TG-09 – Guidance)

[9]" *'combustion' means any oxidation of fuels, regardless of the way in which the heat, electrical or mechanical energy produced by this process is used, and any other directly associated activities, including waste gas scrubbing*" (Definition from Article 3(t) in DIRECTIVE 2003/87/EC, 2013)

capacity is the potential capacity of a plant under maximum possible utilization. Therefore, a plant falls under EU ETS regulation as soon as its installed capacity crosses the regulatory threshold, regardless of whether its actual operational capacity is lower. This means that firms cannot easily circumvent the regulation by adjusting their plant's capacity, especially in the short term, if the plant's activities are regulated by the EU ETS and the installed capacity surpasses the threshold. This characteristic of the EU ETS creates an ideal scenario for implementing a regression discontinuity design.

1.3 Data

This section introduces the multiple datasets used for the analysis and describes in details how different datasets were merged and cleaned.

1.3.1 Major Datasets

EU ETS Data

The EU ETS dataset used in this analysis is sourced from EUETS.INFO[10], which compiles its information from the European Union's Transaction Log (EUTL)[11]. The EUTL serves as the primary tool for reporting and monitoring within the EU ETS, offering public access to data on annual compliance of regulated entities, participant account details, and transaction records of emission allowances. While the EU ETS data is openly available on EUTL, direct access can be challenging due to the data format and the disconnected nature of different tables. EUETS.INFO addresses this by providing a cleaned, relational database that maintains all original information while enhancing accessibility and usability.

[10] EUETS.INFO is a project led by Dr. Jan Abrell, aiming to make the EUTL data more accessible. Link to EUETS.INFO: https://www.euets.info/

[11] Link to EUTL: https://ec.europa.eu/clima/ets/

Power Plants Data

I obtained data on European power plants from the S&P Global Market Intelligence World Electric Power Plants Database (WEPP). WEPP compiles data from various sources, including direct surveys, power company financial reports and web pages, power plant data from government ministries, and media outlets in the trade and business sectors. It has a comprehensive coverage of worldwide electric power generating units[12], especially units for medium- and large-sized power plants. However, WEPP's coverage for small units, specifically those with a generating capacity under 100 kW, is relatively limited. WEPP provides detailed information at the unit level for each power plant, including ownership, location, technical specifications, and gross generation capacity. Notably, the gross generation capacity in the WEPP database, measured in megawatts electric (MWe), differs from the regulated total rated thermal input (RTI), measured in megawatts thermal (MWt). The former represents the output capacity of a plant, while the latter indicates its input capacity. Due to the lack of available data on plants' input capacity, this study utilizes the output capacity as a key component of its empirical design, which will be elaborated on in Section 1.4.

Emission Data and Financial Data

Company-level emission data comes from S&P Trucost Environmental Data, which documents the environmental impacts (such as GHG emissions, waste generation, air pollutants, etc.) of over 15,000 companies globally, covering approximately 95% of global market capitalization. Trucost updates this data annually, relying on both company disclosures and its own modeling to address gaps in self-disclosure. Additionally, Trucost assigns a disclosure score to each firm, ranging from 0 to 100%, which reflects the extent of their self-disclosure. This disclosure score can be used for controlling potential biases related to disclosure in subsequent analyses. An advantage of this dataset is its coverage of both direct environmental impacts of firms and their indirect impacts along supply chains.

[12]By general definition, a power plant unit is a prime mover such as a turbine, engine or a moter, and a power plant can have many units.

This study focuses specifically on Scope 1 and Scope 2 GHG emissions. According to the Greenhouse Gas Protocol[13], Scope 1 GHG emissions are direct emissions from sources owned or controlled by the firm[14], whereas Scope 2 emissions pertain to indirect emissions from the consumption of purchased electricity. Scope 3 emissions, which include indirect emissions across a firm's entire value chain, are not considered due to limited reporting. To complement this environmental data, financial information for the firms is obtained from S&P Capital IQ. This allows for a direct match with the Trucost data using a common identifier from the data provider.

Firm Relationship Data

Firm relationship data is obtained from the FactSet Revere Supply Chain Relationship database, which tracks over 25,000 public companies worldwide, offering historical data dating back to 2003. This database gathers relationship information from key public sources, including SEC filings, investor presentations, and press releases, categorizing them into four main groups: competitors, suppliers, customers, and strategic partners. The company relationships in this database are updated daily to reflect the latest company activities and developments.

1.3.2 Data Cleaning

Merging multiple datasets for analysis poses a significant challenge in this study, largely due to the lack of common identifiers across most datasets. An exception is the financial data from Capital IQ and Trucost's emission data, which share identifiers as they originate from the same provider. For datasets without common identifiers, a consistent matching strategy is employed, based on firm or plant names. This involves first standardizing the names in each dataset, followed by an initial attempt at exact matching. Names that do not match precisely are

[13]Developed by the Greenhouse Gas Protocol Initiative, a partnership involving businesses, NGOs, and governments. More information: https://ghgprotocol.org/

[14]Excludes direct emissions from biomass combustion, which are reported separately.

then subjected to fuzzy matching. A critical final step is the manual review and verification of all matches to ensure accuracy. This meticulous process results in the creation of a linking file, facilitating the seamless merging of datasets for future analyses.

The linking file generated in the previous step enables connecting Trucost firms with their corresponding WEPP plants. This matched set from WEPP encompasses both EU ETS-regulated and non-regulated plants. Plant regulation status is determined by matching WEPP data with EU ETS installations by name and year, with a plant considered regulated if it matches an EU ETS installation in a specific year. Subsequently, financial data from Capital IQ, using shared identifiers with Trucost, is integrated into this data assembly. In line with the focus of this paper on the first three phases of the EU ETS, any WEPP plants that began operations post-2020 are excluded. Building on the matched data, this study then aggregates the relevant plant information to the firm level, synthesizing key variables including total generation capacity, plant count, and regulatory status. Firms are classified as regulated if they own at least one plant under EU ETS jurisdiction. The resulting dataset, comprising 1,321 firms from Trucost and their corresponding WEPP plants with integrated firm-level financials, emissions, plant information, and regulatory status, lays the groundwork for the ensuing analysis, subject to further refinement and validation.

Relationship data from FactSet Revere covers 1,073 firms from the previously matched dataset. In my analysis, I focus on direct links between firms and exclude competitor-type relationships. I consolidate these firm relationships from a firm-peer-year basis to a firm-year basis, tallying the total number of connections for each type of relationship. Furthermore, I assume the continuity of a reported relationship between two firms from its first to its last reported year, disregarding any unreported periods in between. For example, if firm A lists firm B as a supplier from 2004 to 2006 and then again from 2010 to 2012, with no reports in the intervening years, I treat firm B as firm A's supplier continuously from 2004 through 2012. This assumption is reasonable considering that firms may maintain interactions even if a formal relationship isn't consistently reported.

In constructing the sample for the regression discontinuity (RD) analysis, I selected only those firms, out of the 1,321-firm sample, whose all ETS-regulated plants regulate based on thermal input capacity, due to the unavailability of data on plant production capacities. For instance, a firm with a power plant regulated by thermal input capacity and a ceramic production plant regulated by production capacity is excluded from the RD sample. Additionally, for simplicity, the analysis is confined to firms that came under EU ETS regulation starting in 2005. For each qualifying firm, I included a variable representing the gross generation capacity of its largest eligible plant in 2004, the year preceding the EU ETS's launch. This variable serves as the basis for creating the running variable in the RD design, with a plant qualifying if its activities are regulated based on thermal input capacity. The final sample comprises 546 unique firms, amounting to 8,736 firm-year observations from 2005 to 2020. However, subsequent analyses may involve imbalanced samples due to occasional missing values in certain outcome variables across different years.

1.4 Empirical Strategy

A naive comparison between outcome variables, such as GHG emissions from firms with and without EU ETS-regulated plants, can be misleading. This is because regulated and unregulated firms may differ significantly, and some firm characteristics might be correlated with both the regulatory status and the outcome of interest. For example, larger, publicly-traded, high-emission firms are not only more likely to be regulated but also more susceptible to external pressures, which may make them more likely to reduce their GHG emissions. Therefore, drawing definitive conclusions on the impacts of environmental regulation solely based on observed reductions in GHG emissions relative to unregulated counterparts is unwarranted. A more rigorously designed identification strategy is needed.

In light of the EU ETS regulatory features, an ideal approach would involve a multi-dimensional sharp RD design, with the score(s) of a firm being the regulated thresholds specified by different measures of plant productivity capacity. However, this approach is hindered by the unavailability of data on plant productivity capacities. To address this challenge, I focus on firms with plants performing activities regulated solely based on total rated thermal input, and use the gross generation output capacity of each firm's largest plant as the score to conduct a fuzzy-RD design. While the output capacity (MWe) is not the input capacity (MWt) regulated by EU ETS, the two capacities are mechanically linked by the plant's efficiency, i.e., the output-to-input capacity ratio[15]. Therefore, although the regulated input capacity (MWt) is not observed, one can use the output capacity (MWe) as the score to conduct a fuzzy-RD analysis. The corresponding threshold will then be a left-shift of the original 20MWt regulation threshold and can be found through graphing the regulation probability against the output capacity.

To understand this, first consider the probability of treatment at the plant level. Let $Pr(T|MWe)$ be the probability of treatment for a plant given its output capacity (MWe), and let η denote the efficiency of a plant, where

$$\eta = \frac{Output\ Capacity\ (MWe)}{Input\ Capacity\ (MWt)}.$$

The probability of treatment conditioned on output capacity $Pr(T|MWe)$ is equivalent to

$$Pr(MWt \geq 20|MWe) = Pr(\frac{MWe}{\eta} \geq 20|MWe) = Pr(\eta \leq \frac{MWe}{20}|MWe)$$

The last equation $Pr(\eta \leq \frac{MWe}{20}|MWe)$ is essentially the conditional CDF of plant

[15]For instance, a 100 MWe coal-fired power plant with an efficiency of 50% will be rated at 200 MWt, as it requires 200 MW of heat from burning coal for every 100 MW of electricity it produces. This means that it generates 100 MW of waste heat, usually into a large body of water or the atmosphere. (From Energy Education: https://energyeducation.ca/encyclopedia/Megawatts_electric; R. Wolfson, "Energy and Heat," in Energy, Environment and Climate, 2nd ed. New York, U.S.A.: Norton, 2012, pp. 86-87)

efficiency. Let G denote the distribution of η, and assume that $\eta \sim G$ on $[\underline{\eta}, \overline{\eta}]$, where $\underline{\eta}$ and $\overline{\eta}$ are lower and upper bound of efficiency[16], respectively. Then $Pr(T|MWe)$ can be written as a step function of the output capacity MWe:

$$Pr(T|MWe) = \begin{cases} 0 & \frac{MWe}{20} < \underline{\eta} \\ Pr(\eta \leq \frac{MWe}{20}|MWe) = G(\frac{MWe}{20}|MWe) & \underline{\eta} \leq \frac{MWe}{20} \leq \overline{\eta} \\ 1 & \frac{MWe}{20} > \overline{\eta} \end{cases}$$

Whether there are any jumps in the probability of treatment depends on the joint distribution of plant efficiency η and the output capacity. Although research (e.g. Bejan et al., 2017) shows a positive correlation between a power plant's efficiency and its output capacity, it is reasonable to assume that η is almost independent and identically distributed within a small range around a given output capacity. Therefore, any noticeable jumps in $Pr(T|MWe)$ are likely due to jumps in the distribution of η, $G(\eta)$. Clearly, if η has a discrete distribution, we can expect multiple jumps in $Pr(T|MWe)$, with the largest occurring where η's mode is. This corresponds to an output capacity of $20\eta_{mode}$, a left-shift from the original 20MWt threshold, considering η ranges between 0 and 1. However, if η is continuously distributed, the treatment probability $Pr(T)$ becomes a continuous function of output capacity, exhibiting kinks at $20\underline{\eta}$ and $20\overline{\eta}$, rather than distinct jumps. In such cases, a regression kink design is more appropriate than a regression discontinuity design, due to the absence of a clear discontinuity for any RD designs. Nevertheless, a fuzzy-RD remains a viable approach if η has a sufficiently small variance. This would result in $G(\eta)$ having a steep slope where the probability density of η is highest. In a finite sample, this appears as a discrete jump at $20\eta_{mode}$, similar to the discrete scenario. If the distribution of η satisfies this criterion, conducting a fuzzy-RD around the apparent jump ($20\eta_{mode}$) is still reasonable. This is because, except for plants with output capacities very close to

[16] The efficiency of a combustion unit varies based on the technology and fuel type used. For instance, in 2019, a standard natural gas plant in the United States operated at about 45% efficiency, compared to a typical coal power plant in the U.S., which had an efficiency of around 32%.

$20\eta_{mode}$, a distinct jump in $Pr(T)$ is observable for plants just below and above this threshold, without other plant characteristics abruptly changing around this point.

To assess the feasibility for a potential fuzzy-RD design, I have plotted the probability of treatment against the gross output capacity for all eligible plants in WEPP , as illustrated in Figure 1.3. Eligible plants are those engaged in activities regulated solely by thermal input capacity and use major fuels under EU ETS regulations. However, for plants in WEPP not under EU ETS regulation, the absence of EU ETS-specific activities makes selection based on these activities infeasible. Hence, I utilize the 'business type' variable in WEPP to filter out plants in sectors not regulated by thermal input. Figure 1.3 reveals a significant jump in the probability of treatment around $4MWe$, with further analysis indicating a cutoff at $4.2MWe$[17] This observed discontinuity in the probability of treatment can be used as the output capacity (MWe) threshold for a fuzzy-RD analysis to causally identify the impacts of EU ETS on plant-level outcomes. However, given that most data for this study are at the firm level, and firm-level outcomes are arguably more insightful, it is necessary to adapt this plant-level threshold to the firm level. I achieve this by taking the maximum output capacity across all eligible plants owned by a firm as the firm's score. Assuming continuity in all other firm characteristics besides the probability of regulation at the $4.2MWe$ threshold, the local average treatment effect (LATE) can be identified through a fuzzy-RD analysis[18].

[17]This implies that plant efficiency is most densely distributed around 21%.

[18]For this to be true, the *monotonicity* assumption, as proposed by Angrist and Imbens (1995), is needed. This assumption permits the presence of *always-takers* and *never-takers*, but assumes there are no *defiers*. Under this assumption, the fuzzy-RD estimate recovers the local average treatment effect for the *compliers*.

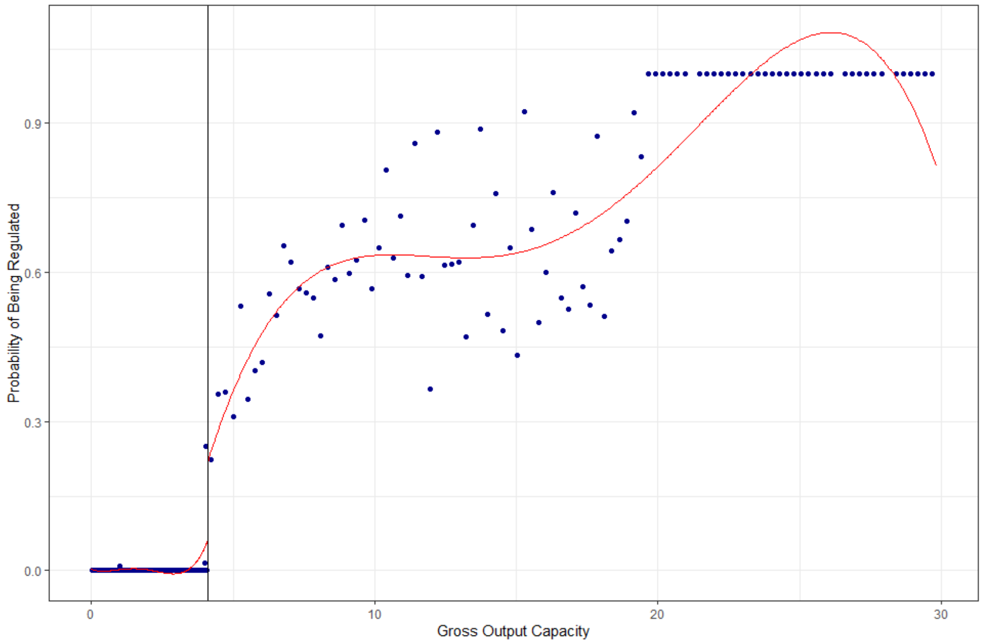


Figure 1.3: Probability of Treatment by Output Capacity

Note: The figure presents the conditional probability of being regulated given the score, $Pr(T|MWe)$, for eligible plants in WEPP with output capacity below $30MWe$. The interval is partitioned into evenly-spaced non-overlapping bins, using method proposed in Cattaneo et al. (2019). There is a clear jump in probability of treatment around $4.2MWe$.

The main analysis of this paper uses the local linear specification as recommended by Gelman and Imbens (2019). The fuzzy RD equations are given below:

$$EUETS_i = \alpha_0 + \alpha_1 Score_i + \alpha_2 Score_i \times \mathbf{1}\{Score_i \geq 0\} + \alpha_3 \mathbf{1}\{Score_i \geq 0\} + \nu_i \tag{1.1}$$

$$Y_{it} = \beta_0 + \beta_1 Score_i + \beta_2 Score_i \times \mathbf{1}\{Score_i \geq 0\} + \beta_3 EUETS_i + \delta_t + \epsilon_{it} \tag{1.2}$$

Equation (1.1) estimates the first-stage effects, where $EUETS_i$ is an indicator that equals to 1 if a firm is regulated by EU ETS starting in 2005. $Score_i$ is the 2004 baseline output capacity of a firm's largest plant normalized by subtracting $4.2MWe$. Since only firms regulated from the beginning of EU ETS and firms that are never regulated are included, both $EUETS_i$ and $Score_i$ are not time varying. Y_{it} in equation (1.2) is the outcomes of interest for firm i in year t, where t spans from 2005 to 2020. The year fixed effect δ_t is included to absorb time-varying factors common to all firms. As pointed out by Cattaneo et al. (2019), if the RD design is valid, the above specification is sufficient without including any covariates. Therefore, I stick to the above basic specification in this paper for simplicity.

The coefficient β_3 captures the LATE of EU ETS on the outcomes of interest. This can be interpreted causally, provided that the assumption of monotonicity is met and all other firm characteristics exhibit continuity, with the exception of the treatment probability, at the threshold. Given this study's institutional setup, monotonicity, which precludes the existence of defiers, is naturally satisfied. To verify the continuity assumption, I conducted balance checks for predetermined firm characteristics and a density test for the running variable, following guidelines from Cattaneo et al. (2023). Table 1.1 presents the predetermined firm characteristics below and above the observed threshold $4.2MWe$. Despite significant differences in the means of most characteristics on either side of the threshold, largely due to their positive correlation with maximum plant output capacity, the RD estimations (the last two columns) do not reject the null hypothesis of no treatment effect on these predetermined firm characteristics. The graphical version of the balance check is presented in Figure 1.4, where firms with scores less than 15 are included. The figure illustrates that while most predetermined characteristics correlate positively with the score, no significant discontinuity is observed at the threshold. For the density test, I applied the local-polynomial method proposed by Cattaneo et al. (2020). The test yields a p-value of 0.6843, indicating that the null hypothesis of continuous score density at the cutoff is not rejected. Figure 1.5 provides a graphical representation of the density test, presenting both a histogram of the score and the density estimate with 95% confidence intervals. As can be seen in (b), the estimated density near the cutoff is nearly smooth.

Table 1.1: Summary Statistics for Balance Check

	Full	Above	Below	Difference of means	p-value	RD estimate	p-value on RD estimate
ln Total Assets ($M)	6.861	7.358	6.422	0.936	0.0002	-0.552	0.678
ln Revenue ($M)	6.519	6.990	6.112	0.878	0.0001	0.161	0.890
ln Net Income ($M)	3.616	4.044	3.239	0.805	0.0039	-0.273	0.861
Debt to Equity Ratio	1.282	1.402	1.176	0.226	0.3770	-0.002	0.998
ln Capital Expenditure ($M)	3.594	4.108	3.146	0.962	0.0001	0.072	0.954
Total Output Capacity (MWe)	168.434	217.475	122.008	95.467	0.0340	-98.085	0.347
Number of Plants	1.231	1.607	0.908	0.699	0.0006	-0.936	0.157
Number of Links	36.045	44.533	29.037	15.497	0.0312	-3.266	0.909
Disclosure Score	51.379	54.009	49.123	4.886	0.2240	4.206	0.840

Notes: The table presents mean values for pre-EU ETS (before 2005) firm characteristics. Column 1 presents the unconditional means for all matched firms with scores less than 15. Column 2-3 present the unconditional means for firms below and above the observed jump ($4.2MWe$). Column 4 shows the difference of the means across columns 2 and 3, while Column 5 presents the p-value of the difference of means. Column 6-7 present the sharp regression discontinuity estimates and their corresponding p-values for pre-determined firm characteristics, using mean squared error optimal bandwidths and robust bias correction approach following Calonico et al. (2014). The heteroskedasticity robust standard errors are used.

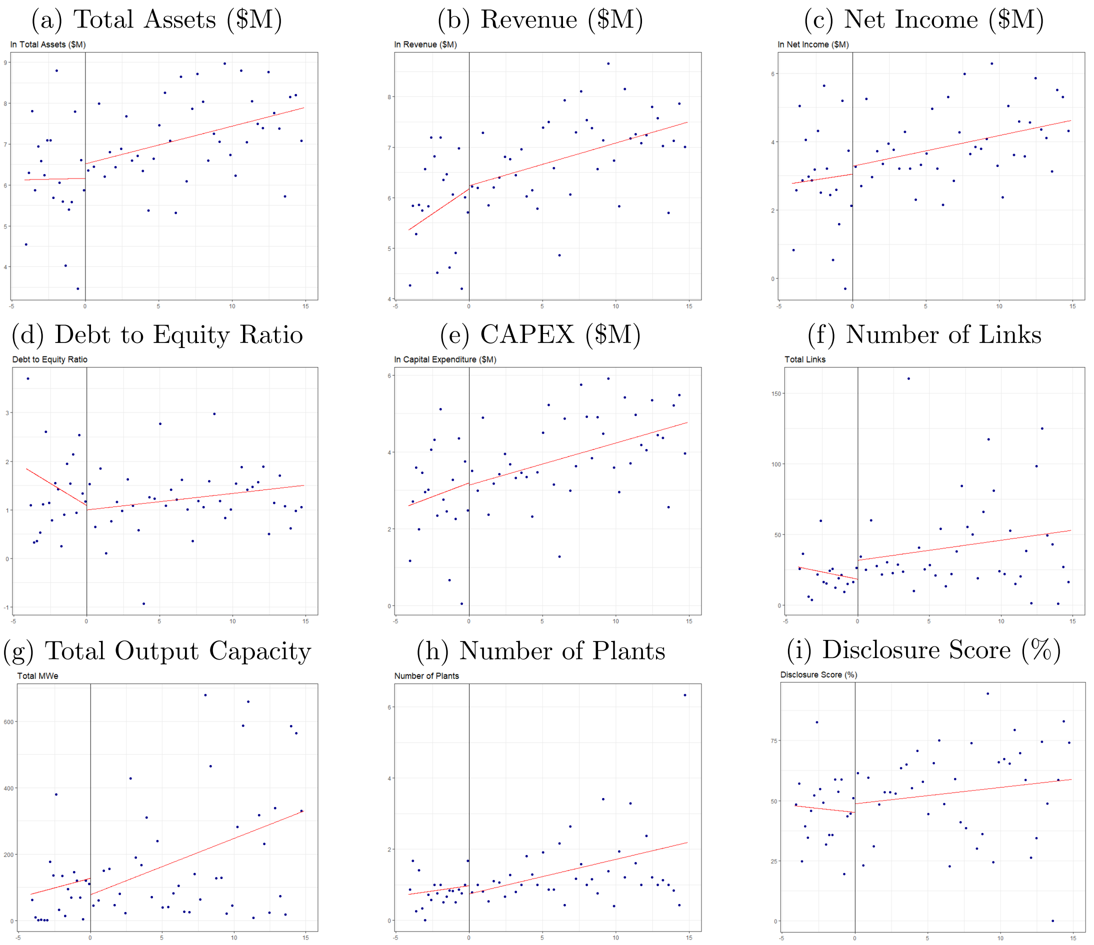


Figure 1.4: Balance Check of Baseline Firm Characters

Note: The figure plots the sharp-RD results in Column 6-7 from Table 1.1 for all pre-EU ETS firm characteristics. The vertical line in each sub-figure is the observed threshold $4.2MWe$, with the score normalized to 0. A linear regression is performed separately for firms on each side of the threshold.

(a) Histogram of the Score (b) Density of the Score

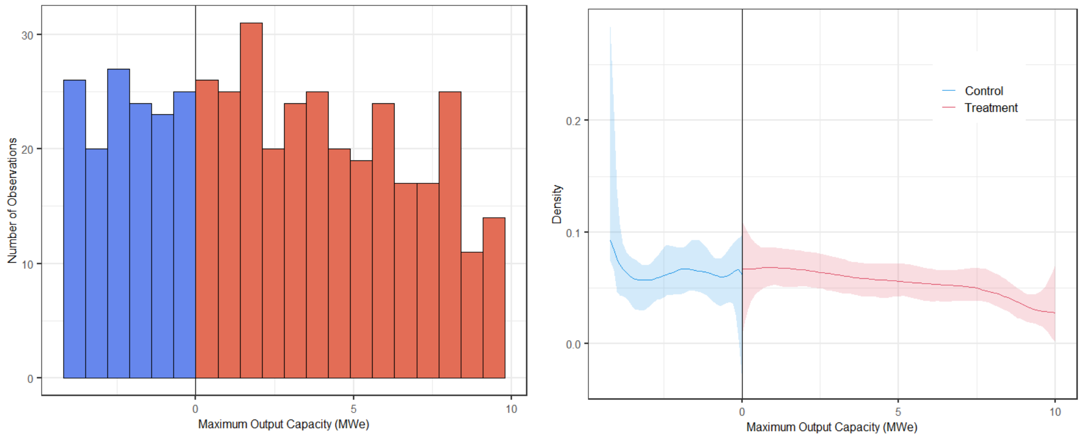


Figure 1.5: Histogram and Estimated Density of the Score

Notes: The figures provide a graphical representation of the continuity in density test, in both (a) histogram of the score and (b) the density estimate with shaded 95% confidence intervals. The score of each firm is the normalized maximum plant output capacity in 2004, which is obtained by deducting $4.2MWe$ from the original value. The vertical line at 0 in both (a) and (b) is where the $4.2MWe$ threshold lies, normalized to 0. The local-polynomial density estimator following Cattaneo et al. (2020) is -0.4065 with a p-value of 0.6843.

Figure 1.6 displays the proportion of firms subject to EU ETS regulation across different score bins. Notably, a distinct jump in the probability of receiving treatment is observed at the $4.2MWe$, which is normalized to 0. This threshold corresponds to the one identified in Figure 1.3. Furthermore, Table 1.1 details the first-stage estimates of the coefficient α_3, calculated using a variety of bandwidth options. Both conventional and robust bias-corrected estimates, as suggested by (Calonico et al., 2014), are included. In line with the graphical representation in Figure 1.6, there is a marked discontinuity in the probability of treatment when crossing the $4.2MWe$ threshold, with an increase of at least 40 percentage points. This significant jump indicates a robust first-stage effect in the regulatory impact of the EU ETS on firms.

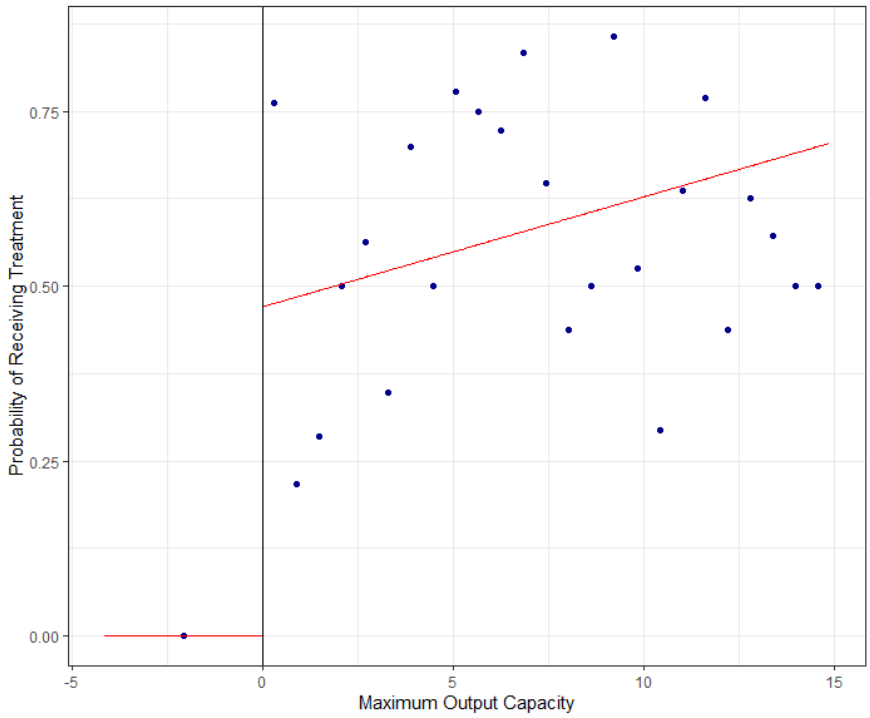


Figure 1.6: First-stage Fuzzy RD Graph

Note: The figure plots the probability of being regulated against the score, i.e., the normalized maximum plant output capacity in 2004. The vertical line at 0 is the normalized threshold $4.2MWe$ observed in the full sample of eligible plants in WEPP, as shown in Figure 1.3. The sample contains firms with score less than 15 or with the output capacity of the largest plant less than $19.2MWe$.

Table 1.2: First Stage: Treatment on the Output Capacity (MWe) of the Largest Plant

	± 1.5	± 2.5	± 4.2	± [-4.2, 6.5]	[-4.2, 7.5]	[-4.2, 9.5]
Conventional	0.656***	0.585***	0.501***	0.421***	0.403***	0.416***
	(0.167)	(0.118)	(0.090)	(0.073)	(0.069)	(0.061)
Robust	0.402**	0.698***	0.604***	0.561***	0.525***	0.434***
	(0.202)	(0.199)	(0.138)	(0.107)	(0.100)	(0.090)
Observations	800(L) 897(R)	1346(L) 1473(R)	2210(L) 2353(R)	2210(L) 3490(R)	2210(L) 3890(R)	2210(L) 4610(R)
Polynomial	1	1	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	Manual	Manual	Manual	Manual	Manual	Manual

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the first-stage estimates of the probability of treatment when the maximum output capacity of a firm is above the observed $4.2MWe$ threshold. The dependent variable is an indicator that equals 1 if a firm is regulated under EU ETS. The first to the third columns present results for firms whose largest eligible plants having output capacity that is 1.5, 2.5 and 4.2 below and above the threshold, while the last three columns expand the right side of the threshold to include firms whose largest eligible plants fall below +6.5, +7.5 and +9.5 above the threshold, respectively. Both estimates using conventional inference and estimates using robust bias-corrected inference are reported.

1.5 Empirical Results

1.5.1 Summary Statistics

Table 1.1 displays the summary statistics for the outcome variables studied in this paper. The emission outcome variables include both direct (scope 1) and indirect (scope 2) emissions. The unit of the absolute amount is tonnes of carbon dioxide equivalent, or tCO2e; while the emission intensity is calculated as the absolute amount of emissions divided by the firm revenue in millions of dollars. To assess the impacts of the EU ETS on firms' financial performance, the revenue, net income and capital expenditure (all in millions of dollars) are selected as the outcome variables. Logarithmic scale is used for both the emission and financial outcome variables because the distribution of pre-scaled variables are right-skewed. To deal with the negative values in net income when taking logs, I first normalize the net income for each firm to above 0 and then take logs. Mathematically, for company i, $\ln(Net\,Income_i) = \ln(Net\,Income_i - \min(Net\,Income) + 1)$, where $\min(Net\,Income)$ is the minimum net income across all firms and all periods.

To estimate the impacts on firm networks, I investigate the geographic distribution of their networks and compositions of their technological relationships. Specifically, *No. of EU Links* shows the total number of business relationships with European firms for a firm in a given year, where business relationships include customers, suppliers and strategic partners[19]. *No. of EU Customers (Suppliers)* measures the total number of European customers (suppliers) a firm has in a given year. The *non-EU Links* are similarly defined. The *Share of EU Links* is calculated as *No. of EU Links* divided by the sum of *No. of EU Links* and *No. of non-EU Links*; while the *Share of EU Customers (Suppliers)* is calculated as *No. of EU Customers (Suppliers)* divided by the sum of *No. of EU Customers (Suppliers)* and *No. of non-EU Customers (Suppliers)*. I also examine the regulatory

[19] Technological relationship is a type of strategic partnership. Other types of relationships included as strategic partners are: manufacturing, marketing, distribution, investment, joint venture, integrated product offering. To better capture the geographic dependency of the supply chains, the investment-type of relationships are excluded.

impacts on the number of technology relationships and the share of technological relationships in all types of relationships (excluding investment-type). There are two types of technological relationships: one is licensing arrangement where one firm licenses products, patents, intellectual property, or technology from the other firm (termed *License-From*) or vice versa (*Licence-To*), and the other is technology partnership where two firms engage in a collaborative research and development activities.

Table 1.3: Summary Statistics for Outcome Variables

Outcome Variables:	Minimum	25th Percentile	Median	75th Percentile	Maximum	Mean	Standard Deviation
Emissions Outcomes:							
ln Scope 1 (abs)	3.395	10.372	11.638	12.992	18.642	11.615	2.075
ln Scope 1 (int)	-4.463	3.268	5.179	6.275	10.493	4.766	2.085
ln Scope 2 (abs)	0.007	8.538	10.189	12.124	17.939	10.083	2.897
ln Scope 1&2 (abs)	4.234	10.942	12.098	13.547	18.679	12.160	2.004
ln Scope 1&2 (int)	-1.533	4.015	5.524	6.467	10.236	5.256	1.705
Financial Outcomes:							
ln Revenue	-2.967	5.340	7.100	8.613	12.852	6.849	2.482
ln Net Income	0.000	9.835	9.837	9.851	11.115	9.860	0.147
ln Capital Expenditure	0.001	2.269	4.108	5.789	10.541	4.071	2.274
Supply Chain Outcomes - Geographic Distribution:							
No. of EU Links	0	4.000	14.000	40.000	374	30.291	40.622
No. of non-EU Links	0	4.000	15.000	41.000	374	30.541	40.694
Share of EU Links	0	0.211	0.417	0.647	1.000	0.437	0.278
No. of EU Customers	0	0.000	2.000	9.000	232	6.918	11.739
No. of non-EU Customers	0	0.000	5.000	18.000	597	14.211	25.835
Share of EU Customers	0	0.132	0.324	0.574	1.000	0.382	0.314
No. of EU Suppliers	0	1.000	5.000	19.000	227	15.911	25.432
No. of non-EU Suppliers	0	2.000	8.000	26.000	472	25.490	48.183
Share of EU Suppliers	0	0.167	0.429	0.667	1.000	0.438	0.309
Supply Chain Outcomes - Technological Relationship:							
No. of Technology Links	0	0.000	3.000	14.000	500	12.987	25.525
Share of Technology Links	0	0.000	0.083	0.182	1.000	0.125	0.151
No. of License-To Links	0	0.000	0.000	1.000	68	2.147	6.356
No. of License-From Links	0	0.000	0.000	1.000	72	2.003	7.512
No. Tech-Collaboration Links	0	0.000	2.000	10.000	407	8.843	18.332

Notes: This table presents the summary statistics for the outcome variables evaluated in the regression analyses. Outcome variables measure three aspects of a firm: GHG emissions, financial performance, and supply chain composition.

1.5.2 Main Results

The findings from the primary analysis outlined in the preceding section are detailed in Tables 1.4 through 1.7. Recognizing the influence of bandwidth selection on RD results, I adhere to the guidelines set by Cattaneo et al. (2019) and employ a bandwidth that minimizes the mean squared error (MSE). This is paired with a triangular kernel function for each specific analysis. The chosen MSE-optimal bandwidths aim to reduce the MSE of the RD estimators for a given polynomial order and kernel function. The formula for determining MSE-optimal bandwidths involves the outcome variable Y, as explained by Imbens and Kalyanaraman (2012), leading to varying bandwidths for different regression analyses based on the respective outcome variables. Consequently, each estimate is derived from a distinct set of observations. To address potential inconsistencies arising from this and to conduct a thorough robustness check, I also present estimates using various fixed bandwidths across different outcome variables in Appendix A.2.

Table 1.4: Impact of EU ETS on GHG Emissions

	Full	Phase 1	Phase 2	Phase 3
Scope 1 (Absolute)	-1.093	-1.022	-0.916	-1.411
	(0.941)	(0.783)	(0.931)	(1.488)
Observations	1778(L) 6372(R)	273(L) 1194(R)	483(L) 1990(R)	1100(L) 3188(R)
Bandwidth Length	[-3.41, 14.89]	[-2.73, 14.89]	[-2.92, 14.89]	[-4.16, 14.89]
Scope 1 (Intensity)	-3.095*	-3.338**	-3.191**	-2.599**
	(1.654)	(1.672)	(1.602)	(1.202)
Observations	2194(L) 5074(R)	300(L) 654(R)	578(L) 1405(R)	924(L) 3188(R)
Bandwidth Length	[-4.16, 10.55]	[-3.15, 6.53]	[-3.62, 8.98]	[-3.57, 14.89]
Scope 2 (Absolute)	1.242*	2.043*	2.075**	1.339*
	(0.749)	(1.045)	(1.022)	(0.790)
Observations	1732(L) 1999(R)	300(L) 765(R)	460(L) 1306(R)	860(L) 881(R)
Bandwidth Length	[-3.3, 3.52]	[-3.19, 7.86]	[-2.76, 8.25]	[-3.25, 3.12]
Scope 1 & 2 (Absolute)	-0.489	-0.700	-0.269	0.155
	(0.900)	(0.934)	(0.912)	(0.740)
Observations	2143(L) 2429(R)	399(L) 510(R)	563(L) 951(R)	884(L) 1175(R)
Bandwidth Length	[-4.16, 4.37]	[-4.16, 4.94]	[-3.5, 5.7]	[-3.41, 4.17]
Scope 1 & 2 (Intensity)	-1.487	-2.520	-2.074	-0.753
	(1.956)	(1.885)	(1.910)	(1.361)
Observations	2079(L) 3913(R)	399(L) 603(R)	568(L) 1221(R)	739(L) 1760(R)
Bandwidth Length	[-4.06, 7.56]	[-4.16, 6.07]	[-3.56, 7.55]	[-2.77, 6.76]
Polynomial	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	msetwo	msetwo	msetwo	msetwo

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents regression discontinuity estimates of the impact of the EU ETS on firms' GHG emissions in logarithmic scale. The unit of all pre-scaled absolute amounts of emissions is tonnes of carbon dioxide equivalent (tCO2e), while the unit of the corresponding carbon intensity is $tCO2e/US\$mnRevenues$, calculated by dividing the absolute amount of emissions by a firm's annual consolidated revenues in millions of US dollars. MSE-optimal bandwidths are used with a triangular kernel. The inference uses a robust bias correction approach, with heteroskedasticity-robust errors clustered at the firm level.

Table 1.4 details the effects of the EU ETS on firms' direct (Scope 1) and indirect (Scope 2) GHG emissions. All outcome variables are in logarithmic scale. The first column shows the results for the entire sample period, spanning 2005 to 2020. Columns 2 to 4 break down these results into the different phases of the EU ETS. In comparison with non-regulated firms, those under EU ETS regulation exhibit over a 60% reduction in absolute Scope 1 emissions during the initial three phases, although this reduction is not statistically significant. Notably, there is a substantial reduction in Scope 1 emission intensity among regulated firms, a more than 90% reduction relative to their unregulated counterparts. The drop in emission intensity aligns with the results found by Petrick and Wagner (2014), who observed a significant decline in the *growth rate* of emission intensity using data from German manufacturing plants. The marked and significant decline in Scope 1 emission intensity in my study, however, is primarily attributable to firms located further right of the cutoff. This is evidenced in Tables A.2.3 to A.2.6 in Appendix A.2, where analyses utilizing different bandwidths are displayed.

Contrarily, the results indicate a marked increase in Scope 2 emissions among regulated firms, more than doubling in amount compared to their unregulated counterparts. This substantial increase in Scope 2 emissions remains consistent across various bandwidth choices, as detailed in the tables in Appendix A.2. To assess whether the reduction in Scope 1 and the concurrent rise in Scope 2 emissions are attributable to different firms, the last two blocks of Table 1.4 present the effect on the combined Scope 1 and Scope 2 emissions. While the reduction in combined Scope 1 and Scope 2 emissions is statistically insignificant, its smaller magnitude relative to the reduction in Scope 1 emissions alone suggests that some firms might be mitigating their direct emissions not only through technical improvements but also by redistributing emissions throughout their supply chains. These observations provide a nuanced perspective compared to some earlier studies, which suggested no significant transfer of direct emissions outside the EU by regulated firms, either within the same firms (Dechezleprêtre et al., 2022) or to external entities (Naegele and Zaklan, 2019). However, recent sector-level research by Böning et al. (2023) has indicated some evidence of carbon leakage to unregulated countries, adding complexity to the understanding of emissions redistribution under the EU ETS.

Table 1.5 illustrates the effects of the EU ETS on the financial performance of firms. Notably, firms covered by the EU ETS exhibit an increase in revenue, but these results are somewhat inconsistent, with only the estimates for the entire sample period reaching statistical significance at the 90% confidence interval. Additionally, the study finds no notable effects of the EU ETS on the net income and capital expenditures of these firms. These outcomes are in line with previous research, suggesting that the EU ETS, while influential in some financial aspects, does not substantially alter overall firm profitability.

Table 1.5: Impact of EU ETS on Firm Financials

	Full	Phase 1	Phase 2	Phase 3
Revenue	2.259*	1.657	1.354	1.529
	(1.302)	(1.681)	(1.469)	(1.421)
Observations	1778(L) 6372(R)	411(L) 864(R)	543(L) 1935(R)	868(L) 3188(R)
Bandwidth Length	[-3.46, 14.89]	[-4.16, 9.42]	[-3.34, 14.41]	[-3.28, 14.89]
Net Income	0.073	-0.041	-0.021	0.084
	(0.061)	(0.117)	(0.083)	(0.145)
Observations	2112(L) 2927(R)	324(L) 737(R)	661(L) 1049(R)	970(L) 1593(R)
Bandwidth Length	[-4.16, 5.65]	[-3.78, 8.08]	[-4.16, 6.51]	[-3.8, 6.19]
Capital Expenditure	-0.676	0.454	-0.761	-1.041
	(2.194)	(1.927)	(2.195)	(1.781)
Observations	1319(L) 4239(R)	259(L) 1012(R)	438(L) 941(R)	608(L) 1286(R)
Bandwidth Length	[-2.64, 8.93]	[-3.07, 13.08]	[-3.04, 5.91]	[-2.42, 4.81]
Polynomial	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	msetwo	msetwo	msetwo	msetwo

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents regression discontinuity estimates of the impact of EU ETS on firms' financial performance in logarithmic scale. The unit of all pre-scaled value is millions of US dollars. MSE-optimal bandwidths are used with a triangular kernel. The inference uses robust bias correction approach, with heteroskedasticity-robust errors clustered at firm-level.

To gain a deeper understanding of the EU ETS's effects on firms' supply chains, I examine the geographic composition of customers and suppliers for firms with available supply chain data. The results are shown in Table 1.6. Compared to unregulated firms, regulated firms experience a statistically significant decrease in the number of European peers, whereas their number of non-European peers remains largely unchanged. This reduction in European peers is particularly pronounced during the first two phases of the EU ETS. A similar trend is observed in the relative percentage change in European peers. Throughout the sample period, regulated firms show a significant reduction of over 50% in their European supply chain peers, with a more pronounced 70% decrease in Phase 2. Separate analyses of customers and suppliers reveal that regulated firms have relatively increased their number of European customers, though this change is not statistically significant in terms of percentage. Conversely, there is a suggestive decrease in the number of European suppliers, but this finding is not statistically significant. However, the concluding part of Table 1.6 indicates a significant relative decrease in the percentage of European suppliers for firms covered by the EU ETS, especially in its early years. Overall, the results in Table 1.6 appear to be consistent with the narrative of emissions being shifted across supply chains, as indicated by the growing proportion of non-European suppliers among regulated firms. These non-European suppliers are likely subject to less stringent emission regulations than their European counterparts. Notably, findings from Tables 1.4 and 1.6 imply a diminishing trend in emissions shifting through supply chains in Phase 3. This change could be attributed to the revised regulations in the EU ETS during this phase, which eased conditions for sectors at high risk of carbon leakage while simultaneously tightening restrictions for others[20].

[20] To mitigate carbon leakage, the EU ETS allocates a higher percentage of free allowances to sectors and sub-sectors deemed at significant risk of carbon leakage. The first official list of sectors at significant risk was applied in Phase 3 (https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/free-allocation/carbon-leakage_en).

Table 1.6: Impact of EU ETS on Firm Supply Chains

	Full	Phase 1	Phase 2	Phase 3
No. of Linked European Firms	-15.946	-25.863***	-28.295**	-10.315
	(25.647)	(9.101)	(12.898)	(41.569)
Observations	483(L) 1853(R)	57(L) 478(R)	349(L) 664(R)	265(L) 1058(R)
Bandwidth Length	[-1.42, 5.13]	[-1.25, 14.89]	[-4.16, 7.04]	[-1.37, 4.75]
No. of Linked Non-European Firms	2.094	-1.285	2.397	7.700
	(32.672)	(7.386)	(15.155)	(52.312)
Observations	455(L) 2335(R)	159(L) 478(R)	124(L) 763(R)	266(L) 1384(R)
Bandwidth Length	[-1.35, 6.8]	[-4.16, 14.89]	[-1.3, 8.57]	[-1.34, 6.7]
Linked European Firms (Share)	-0.525***	-0.375	-0.701***	0.114
	(0.203)	(0.583)	(0.251)	(0.268)
Observations	772(L) 1837(R)	69(L) 478(R)	349(L) 569(R)	161(L) 1004(R)
Bandwidth Length	[-2.32, 5.05]	[-1.53, 14.89]	[-4.16, 5.97]	[-0.81, 4.48]
No. of European Customers	13.039**	2.532	5.329**	21.189**
	(5.863)	(2.454)	(2.283)	(9.419)
Observations	503(L) 2963(R)	93(L) 466(R)	147(L) 1097(R)	282(L) 1765(R)
Bandwidth Length	[-1.49, 9.46]	[-2.26, 13.95]	[-1.59, 14.36]	[-1.41, 9]
No. of Non-European Customers	2.542	8.431	9.222	-1.483
	(11.265)	(6.220)	(6.369)	(17.717)
Observations	964(L) 1989(R)	159(L) 456(R)	219(L) 1123(R)	792(L) 1155(R)
Bandwidth Length	[-3.05, 5.76]	[-4.16, 13.22]	[-2.49, 14.89]	[-4.16, 5.28]
European Customers	0.025	-0.002	0.215	0.063
(Share in Customers)	(0.297)	(0.349)	(0.319)	(0.306)
Observations	416(L) 2122(R)	109(L) 376(R)	137(L) 512(R)	189(L) 1199(R)
Bandwidth Length	[-1.44, 7.51]	[-4.09, 14.35]	[-1.83, 7]	[-1.2, 6.46]
No. of European Suppliers	-6.005	-6.861	-6.663	-0.757
	(16.056)	(4.849)	(5.635)	(25.482)
Observations	564(L) 1807(R)	72(L) 437(R)	274(L) 660(R)	282(L) 1048(R)
Bandwidth Length	[-1.74, 5.69]	[-1.72, 14.89]	[-3.5, 8.13]	[-1.5, 5.3]
No. of Non-European Suppliers	-14.578	15.486	2.459	-30.400
	(26.937)	(15.781)	(15.151)	(32.319)
Observations	655(L) 2192(R)	66(L) 437(R)	183(L) 1014(R)	434(L) 913(R)
Bandwidth Length	[-2.14, 7.13]	[-1.61, 14.89]	[-2.22, 14.89]	[-2.26, 4.6]
European Suppliers	-0.161	-0.688**	-0.366*	0.131
(Share in Suppliers)	(0.199)	(0.339)	(0.216)	(0.344)
Observations	472(L) 2057(R)	78(L) 224(R)	169(L) 557(R)	245(L) 1416(R)
Bandwidth Length	[-1.52, 6.69]	[-1.9, 5.95]	[-1.96, 6.62]	[-1.26, 7.73]
Polynomial	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	msetwo	msetwo	msetwo	msetwo

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents regression discontinuity estimates of the impact of EU ETS on firms' supply chain for the subset of firms with supply chain data. The inference uses robust bias correction approach, with heteroskedasticity-robust errors clustered at firm-level.

While emission leakage is one important type of spillovers, over time, technological spillovers driven by firm innovation might become increasingly significant. In the short term, EU ETS-regulated firms might reduce emissions through methods like enhancing operational efficiency or outsourcing high-emission production processes. However, in the long term, innovation in low-carbon technologies is likely to play a pivotal role in emission reduction. Previous research, such as the study by Calel and Dechezleprêtre (2016) using patent data and matching methods, indicates that firms covered by the EU ETS have increased their low-carbon innovations by about 10% in the early stages of the scheme. This paper does not directly contribute new evidence to these findings. Rather, it builds on the understanding that the EU ETS positively influences low-carbon innovation in firms and explores the possibility of technological spillovers within firms' supply chains. Although the literature on innovation spillovers identifies several channels, this analysis focuses specifically on spillovers through technological connections between firms. I consider two firms to be technologically linked if there is a licensing arrangement where one firm licenses products, patents, intellectual property, or technology from the other firm (termed *License-From*) or vice versa (*License-To*), or if the two firms engage in a collaborative R&D partnership. It's important to note that these three types of technological links actually represent voluntary technology transfers, particularly the licensing arrangements which are essentially market transactions. However, as Arqué-Castells and Spulber (2022) demonstrate, the effects of technology diffusing through these voluntary transfers cannot be fully internalized by firms, suggesting that overlooking the technology market might lead to underestimating spillovers and, consequently, the social returns of R&D.

If the EU ETS has indeed motivated regulated firms to innovate in clean technologies, this might also be reflected in their technological linkages. Firstly, firms might venture into new technological domains by establishing connections with entities that possess expertise in these areas. This could result in an increase in newly formed technological links for regulated firms and potentially a rise in dropped links as they move away from previous technological partners. Technology spillovers might occur through licensing agreements among firms. It is hypothesized that regulated firms are more likely to license low-carbon patents from others in the early years of the EU ETS and, over time, possess more clean patents to license out to unregulated firms.

Table 1.7: Impact of EU ETS on Network Composition by Technology Links

	Full	Phase 1	Phase 2	Phase 3
No. of Technological Links	-16.477	3.891	-3.690	-22.486
	(18.442)	(11.854)	(10.889)	(28.789)
Observations	757(L) 1912(R)	81(L) 478(R)	177(L) 787(R)	517(L) 1155(R)
Bandwidth Length	[-2.25, 5.53]	[-1.81, 14.89]	[-1.81, 9]	[-2.59, 5.32]
Technological Links (Share)	-0.118	-0.083	-0.139	-0.082
	(0.086)	(0.171)	(0.122)	(0.100)
Observations	455(L) 1204(R)	66(L) 209(R)	167(L) 387(R)	423(L) 830(R)
Bandwidth Length	[-1.34, 3.24]	[-1.51, 5.1]	[-1.74, 3.61]	[-2.15, 3.58]
No. of Added Technological Links	-2.386	0.122	-1.513	-3.332
	(3.992)	(1.882)	(1.788)	(7.071)
Observations	964(L) 1901(R)	66(L) 469(R)	192(L) 574(R)	664(L) 1155(R)
Bandwidth Length	[-2.93, 5.46]	[-1.52, 14.46]	[-2.07, 6.03]	[-3.36, 5.33]
No. of Dropped Technological Links	-1.754	1.843	-0.364	-2.480
	(2.086)	(1.743)	(1.097)	(3.316)
Observations	915(L) 1937(R)	81(L) 278(R)	129(L) 1123(R)	792(L) 1163(R)
Bandwidth Length	[-2.75, 5.58]	[-1.85, 7.03]	[-1.35, 14.89]	[-4.16, 5.49]
No. of License-To Links	-0.518	1.308	-0.233	-1.368
	(1.936)	(2.069)	(2.012)	(1.760)
Observations	757(L) 1640(R)	81(L) 447(R)	177(L) 976(R)	364(L) 666(R)
Bandwidth Length	[-2.21, 4.4]	[-1.86, 13.03]	[-1.83, 11.64]	[-1.79, 2.95]
No. of License-From Link	2.975	-0.181	-2.094	2.383
	(3.834)	(8.191)	(8.017)	(2.830)
Observations	606(L) 2820(R)	75(L) 478(R)	137(L) 1104(R)	533(L) 1949(R)
Bandwidth Length	[-1.79, 8.71]	[-1.77, 14.89]	[-1.44, 14.71]	[-2.63, 10.23]
License-To Links (Share in Tech)	0.120	0.257	-0.268	0.250
	(0.221)	(0.337)	(0.353)	(0.198)
Observations	811(L) 2023(R)	38(L) 289(R)	183(L) 251(R)	620(L) 1212(R)
Bandwidth Length	[-3.72, 8.62]	[-1.88, 14.89]	[-3.56, 4.08]	[-4.1, 7.53]
License-From Links (Share in Tech)	0.306	0.379	0.666	0.289*
	(0.313)	(0.980)	(0.614)	(0.153)
Observations	317(L) 1489(R)	42(L) 152(R)	80(L) 307(R)	560(L) 1667(R)
Bandwidth Length	[-1.25, 6.04]	[-2.11, 6.73]	[-1.22, 4.81]	[-3.69, 11.48]
Polynomial	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	msetwo	msetwo	msetwo	msetwo

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents regression discontinuity estimates of the impact of EU ETS on firms' technological links for the subset of firms with supply chain data. The inference uses robust bias correction approach, with heteroskedasticity-robust errors clustered at firm-level.

Table 1.7 presents the effects of the EU ETS on firms' technological connections, focusing specifically on *License-From* and *License-To* relationships, as the results for technological collaborations are straightforward to infer. Overall, the

EU ETS's impact on firms' technological links is not significant. There is some indicative evidence that regulated firms increased the turnover of their technological connections in Phase 1, but this lacks statistical significance. Similarly, no significant findings emerge regarding the regulated firms' licensing relationships. The only exception is a noticeable increase in the proportion of *License-From* relationships for regulated firms compared to the control group, significant only in Phase 3. These findings suggest limited technological spillovers through technological links. Nevertheless, these results do not completely eliminate the possibility of innovation spillovers through other channels, nor do they negate the potential impact of the EU ETS in spurring firms to enhance innovation in carbon reduction technologies. For a more thorough analysis, investigating firms' R&D or patent data and other spillover channels would be necessary, but this falls outside the scope of the current study.

1.6 Robustness Check

1.6.1 Econometric Framework

The primary findings in Section 1.5.2 reveal that firms under the EU ETS have managed to reduce their direct emissions compared to a control group, yet this achievement may in part be due to outsourcing emissions across their supply chains. To enhance the robustness of these findings, I leveraged the transition from Phase 2 to Phase 3 of the EU ETS as a natural experiment to examine its impacts on key performance metrics.

This investigation specifically leverages significant regulatory reforms enacted during Phase 3 (2013-2020) of the EU ETS, as detailed in Section 1.2.1. These reforms include the introduction of a single, EU-wide emissions cap, reducing annually by 1.75%, and a shift towards auctioning allowances as the main method of allocation, decreasing the proportion of allowances allocated freely from 90% in Phase 2 to 43% in Phase 3. Figure 1.7 demonstrates a clear reduction in freely allocated allowances at the commencement of Phase 3, highlighting the increased regulatory stringency due to the reforms.

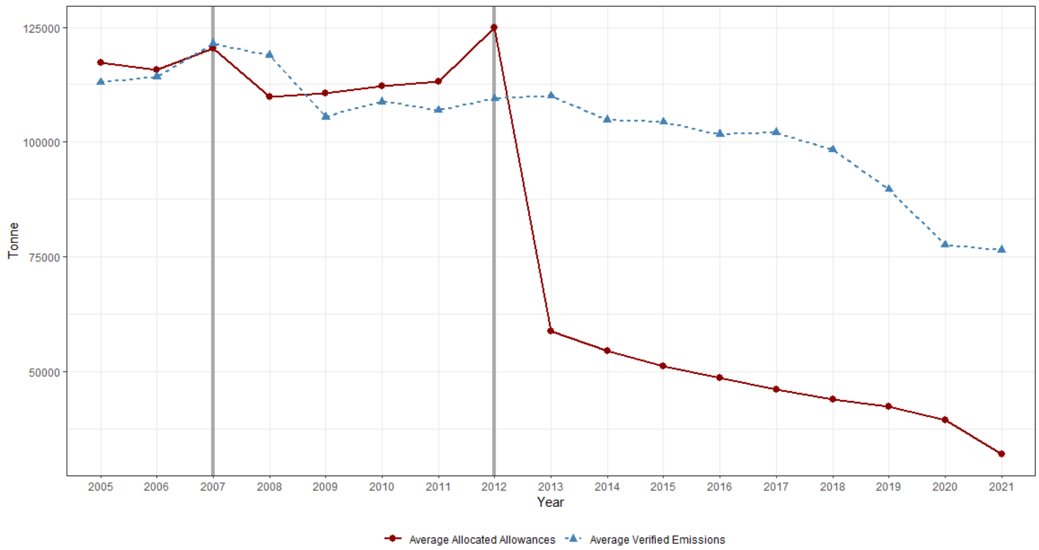


Figure 1.7: Average Annual Emissions and Allowances

Note: The graph displays the average annual verified emissions and average annual free-allocated allowances for all EU ETS regulated installations, excluding airlines. The red line indicates the average number of free-allocated allowances, where each allowance corresponds to 1 tonne of CO_2 equivalent, and the blue dotted line represents the average verified emissions. Two gray vertical lines represent the end of phase 1 and phase 2, respectively.

Additionally, the reduction of free allowances varies across installations. While installations in the power generating sector no longer get any free allowances, installations in other sectors get their free allowances based on a newly introduced benchmarking system. This system sets benchmarks based on the emissions from the top 10% of the most efficient installations producing each product within the EU and EEA-EFTA states. Consequently, installations that achieve these benchmarks are fully compensated for their emissions with free allowances. In contrast, installations that do not meet the benchmarks are allocated fewer allowances, compelling them to either reduce their emissions or purchase additional allowances. This reform not only enhanced the stringency of the regulatory framework but also created variability in the intensity of regulation across different installations and firms. Such variability provides an ideal scenario for conducting a difference-in-difference analysis with continuous treatment. Specifically, I conduct the following analysis for a four-year period from 2012 to 2015:

$$Y_{it} = \delta_t + \alpha_i + \mathbf{X}'\theta + \sum_t \beta_t(\Delta Stringency_{it} \cdot T_t) + \epsilon_{it} \tag{1.3}$$

where Y_{it} represents a particular outcome of interest for firm i in at time t, with t ranging from 2012 to 2015. δ_t and α_i are year and firm fixed effects, respectively, and $\mathbf{X}$ is a vector of control variables.

The coefficients of interest are β_t for the interaction terms $\Delta Stringency_{it} \cdot T_t$ in the summation. T_t is an indicator variable for year t. This specification allows an estimation of time-varying effects after the transition into Phase 3. To measure the change of the EU ETS stringency $\Delta Stringency_{it}$ for a firm, I use the decrease of free allowances relative to the level in 2012, the last year in Phase 2. Specifically, it is calculated as $Base.Allocation_i - Allocation_{it}$, where $Base.Allocation_i$ denotes the total free allowances for firm i in year 2012 across all its EU ETS-regulated plants, and $Allocation_{it}$ is the total free allowances to these plants in year t. The change of stringency $\Delta Stringency_{it}$ in 2012 is therefore zero. By this definition, a higher $\Delta Stringency_{it}$ value indicates a larger reduction in free allowances, and thus, a larger increase in stringency for firm i in year t after the transition to Phase 3. To comply with the tightened regulation, a firm needs to either reduce the direct emissions of its EU ETS-covered plants or purchase additional allowances to offset its direct emissions. A more accurate measure of the increase in regulation stringency should also account for the price of allowances and estimate the impacts of the increase in the marginal cost of emissions on the outcomes of interest as in Martinsson et al. (2024). However, as shown in Figure 1.1, the price of allowances did not change much around the phase transition, and the annual price level of allowances is one of the macro trends absorbed by the year fixed effects. Using $\Delta Stringency_{it}$ is sufficient for the purpose of this study. Another concern is that firms might react by divesting their plants, as documented by Berg et al. (2023), then the above measure of change in regulation stringency will not be accurate. To mitigate this, I also include the change in the number of regulated plants as a control, with the change defined as the number of regulated plants in the current year minus the number of regulated plants in 2012.

1.6.2 Results

The regression results are shown in Table 1.8 and Table 1.9. In both tables, column (1) displays the aggregated results on $\Delta Stringency_{it}$ without interacting with year dummy. Columns (2) to (4) show the coefficients for each year in the early period of Phase 3. The full results, including coefficients on covariates, are also included in tables in Appendix A.3.

Table 1.8: Impacts of Regulation Stringency on Firm Outcomes

	Early Phase 3	Year = 2013	Year = 2014	Year = 2015
	(1)	(2)	(3)	(4)
Emission Outcomes				
Scope1 (abs)	-0.0138***	-0.0020	-0.0150***	-0.0196***
	(0.0022)	(0.0024)	(0.0026)	(0.0025)
Scope1 (int)	-0.0256***	-0.0037	-0.0235***	-0.0397***
	(0.0022)	(0.0025)	(0.0025)	(0.0031)
Scope2 (abs)	0.0767***	-0.0190**	0.0995***	0.1140***
	(0.0096)	(0.0081)	(0.0090)	(0.0141)
Scope 1&2 (abs)	-0.0109***	0.0019	-0.0111***	-0.0181***
	(0.0023)	(0.0025)	(0.0027)	(0.0026)
Scope 1&2 (int)	-0.0227***	0.0003	-0.0196***	-0.0382***
	(0.0024)	(0.0026)	(0.0025)	(0.0032)
Financial Outcomes				
Revenue	0.0045***	0.0006	0.0032***	0.0076***
	(0.0005)	(0.0007)	(0.0005)	(0.0011)
Net Income	0.0073**	0.0023	0.0022	0.0140**
	(0.0033)	(0.0044)	(0.0032)	(0.0059)
Capital Expenditure	-0.0640***	-0.0029	0.0066	-0.1519***
	(0.0060)	(0.0018)	(0.0056)	(0.0148)

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents estimates of the impacts of increase in regulation stringency on firms' GHG emissions and financial performance in logarithmic scale. The unit of all pre-scaled absolute amounts of emissions is tonnes of carbon dioxide equivalent, or tCO2e, while the unit of the corresponding carbon intensity is $tCO2e/US\$mnRevenues$, i.e., calculated as dividing the absolute amount of emissions by a firm's annual consolidated revenues in millions of US dollars. All explanatory variables are standardized. The financial outcome variables are also standardized.

In Table 1.8, we can see that the impacts of increased regulation stringency on firm emissions are consistent with the findings in Table 1.4. A larger increase in regulation stringency results in a statistically significant decrease in regulated firms' Scope 1 emissions, both in absolute terms and intensity. Specifically, a one standard deviation increase in $\Delta Stringency$ leads to a -0.0138 decrease in log absolute Scope 1 emissions, or around a 1.37% decrease relative to the year 2012 level and about a 2.53% decrease in Scope 1 intensity. In contrast, a one standard deviation rise in $\Delta Stringency$ leads to a significant 7.97% increase in absolute Scope 2 emissions. The decrease in Scope 1 and the increase in Scope 2 are mostly driven by results in 2014 and 2015, suggesting a slight delay in response to the increased stringency from firms. The effects on combined Scope 1 and Scope 2 emissions in both absolute terms and intensity are statistically significant and negative. The smaller magnitude relative to the effects on Scope 1 alone confirms the earlier findings that firms reduced their direct emissions partially through shifting across their supply chains. Figure 1.8 provides a graphical version of the impacts of increasing EU ETS stringency on emissions.

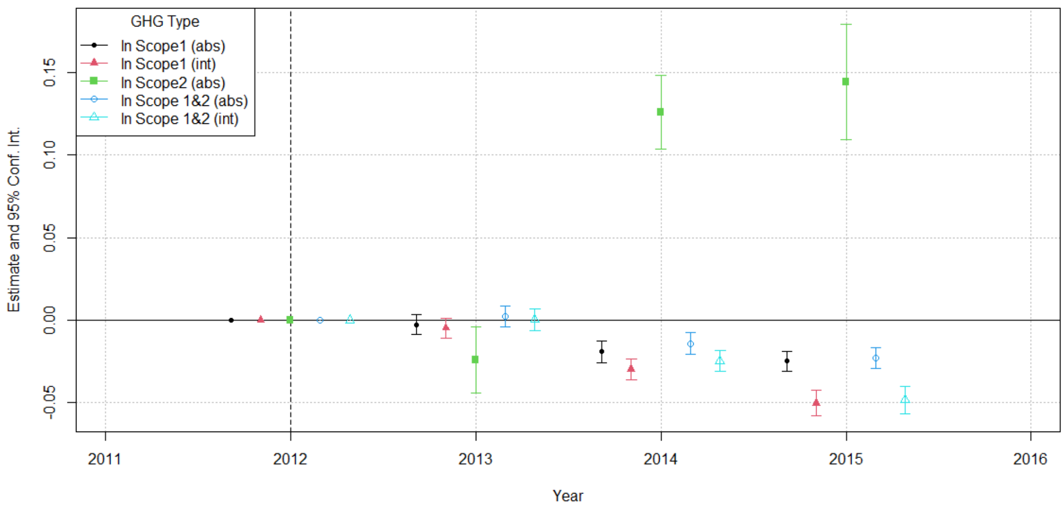


Figure 1.8: Effects of Increased Stringency on GHG Emissions

Note: The figure displays the coefficients for emission outcomes in the first three years of the EU ETS Phase 3. The coefficients capture the change of emission variables relative to their values in 2012, the last year of the EU ETS Phase 2. The vertical line segments denote the 95% confidence interval. To increase readability, coefficients from a specific year are drawn around that year to avoid overlapping.

The second half of Table 1.8 displays the effects of an increase in regulation stringency on firms' financial performance, with both independent and dependent variables standardized. Here, the signs of the estimates are consistent with the signs of fuzzy RD estimates for Phase 3 in Table 1.5. While the coefficients from the fuzzy RD analysis are not statistically significant, the aggregated estimates for the first three years of Phase 3 are statistically significant even though their magnitudes are small. Particularly, a one standard deviation increase in $\Delta Stringency_{it}$ leads to an increase of 0.0045 standard deviations in revenue, 0.0073 standard deviations in net income, and a decrease of -0.064 standard deviations in capital expenditure. However, the significance is mainly driven by results in 2015.

These results are somewhat surprising. Given that buying emission allowances is essentially equivalent to paying a tax, one would expect firms facing larger regulation tightening to become financially worse off as they now need to spend more money to buy extra allowances. One potential explanation is that, since the EU ETS has allowed banking of allowances since 2008, and due to the 2008 financial crisis, there was an oversupply of allowances in Phase 2[21]. Therefore, while the increased regulation stringency in Phase 3 could still have immediate impacts on firms' emissions through the expectation channel, it might not have any immediate negative impacts on firms' financial outcomes. Furthermore, since the results for emissions suggest that part of the reduction in firms' emissions is achieved by shifting their direct emissions across supply chains, the regulatory tightening might have minimal impacts on the financial performance of regulated firms. In addition, as the recent study by Känzig (2023) shows, EU ETS regulated firms passed through the costs to their customers. Given that firms under tighter regulations are those outside of industries that are prone to carbon leakage and firms in the matched sample are mostly big firms with market power, this suggests the demand of their customers is relatively inelastic, and thus the increase in their price due to the pass-through effect will naturally lead to higher revenue. While

[21]For the development of EU ETS, see: https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/development-eu-ets-2005-2020_en

this does not provide a satisfying explanation for the positive impacts of tighter regulation on net income, it at least suggests that increased regulatory stringency does not hurt firms' bottom line in the short run.

The impacts of increased EU ETS stringency on the networks of firms are displayed in Table 1.9. Compared to the results in Table 1.6 for Phase 3, a few estimates have different signs. However, since most estimated effects in Table 1.6 for Phase 3 are not statistically significant, the different signs here might not necessarily pose a contradiction. In fact, most results here are consistent with the overall results of the fuzzy RD analysis. Although firms experiencing more regulatory tightening had increased links with general European business partners and with both European customers and European suppliers, the shares of the links with both general European business partners and with European suppliers are decreasing when $\Delta Stringency_{it}$ increases. These results support the previous argument that regulated firms seem to diversify their supply chain by decreasing their exposure to the EU, where there may be higher transition risks. However, the effects lack economic significance. An increase of one standard deviation in $\Delta Stringency_{it}$ only leads to an average 0.94% decrease in general European business partners and a 0.85% decrease in European suppliers.

The impacts of increased regulation stringency on firms' technological links stand in contrast to the results in Table 1.7 from the fuzzy RD analysis. While there are no statistically significant effects found in the fuzzy RD analysis, here, most of the estimates are statistically significant, albeit with modest magnitudes. Specifically, the second part of Table 1.9 shows that firms facing a larger increase in regulation stringency increase their technological links both in absolute numbers and as a proportion of total links in 2013, the first year of Phase 3. A one standard deviation rise in $\Delta Stringency_{it}$ leads to an increase of 0.7498 in the number of technological links and 0.0046 or 0.46% proportionally. Besides the positive relation between $\Delta Stringency_{it}$ and the stock of technology links, firms experiencing a larger increase in regulation stringency also have a larger turnover of technological connections. A one standard deviation increase in $\Delta Stringency_{it}$

corresponds to an increase of 0.1703 in the number of added technological links and an increase of 0.5116 in the number of dropped technological links during the first three years of Phase 3. These results indicate that firms facing a larger regulatory shock are, on average, not only forming more new technological connections but also dropping more of their existing ones. Such behavior is consistent with the hypothesis that the EU ETS encourages firms to innovate and branch out into new technological areas by forming new partnerships with knowledgeable entities.

Table 1.9: Impacts of Regulation Stringency on Firm Network Outcomes

	Early Phase 3 (1)	Year = 2013 (2)	Year = 2014 (3)	Year = 2015 (4)
Geographic Composition				
No. of European Firms	0.2145***	0.3530***	0.0155	0.2875***
	(0.0433)	(0.0573)	(0.0505)	(0.0517)
European Firms (Share)	-0.0094***	-0.0043***	-0.0125***	-0.0099***
	(0.0009)	(0.0012)	(0.0011)	(0.0012)
No. of European Customers	0.0532*	0.3704***	0.0205	-0.0929**
	(0.0317)	(0.0356)	(0.0327)	(0.0429)
European Customers (Share in Customers)	0.0085***	0.0150***	0.0111***	0.0035**
	(0.0013)	(0.0014)	(0.0013)	(0.0018)
No. of European Suppliers	0.7741***	0.1611***	0.6148***	1.221***
	(0.0660)	(0.0596)	(0.0680)	(0.0759)
European Suppliers (Share in Suppliers)	-0.0085***	-0.0058***	-0.0115***	-0.0077***
	(0.0012)	(0.0014)	(0.0014)	(0.0014)
Technology Composition				
No. of Technology Links	0.0603	0.7498***	0.0480	-0.3010*
	(0.0807)	(0.1587)	(0.0934)	(0.1616)
Technology Links (Share)	0.0009	0.0046***	0.0004	-0.0007
	(0.0009)	(0.0015)	(0.0012)	(0.0013)
No. of Added Technology Links	0.1703***	0.7210***	-0.2897***	0.2152***
	(0.0336)	(0.0644)	(0.0616)	(0.0541)
No. of Dropped Technology Links	0.5116***	0.4665***	0.1719***	0.7876***
	(0.0188)	(0.0383)	(0.0195)	(0.0276)
No. of License-To Links	-0.1148***	-0.1058***	-0.1632***	-0.0838***
	(0.0154)	(0.0209)	(0.0194)	(0.0176)
No. of License-From Links	0.0993***	0.0122	0.1282***	0.1246***
	(0.0178)	(0.0204)	(0.0185)	(0.0172)
No. of Research Collaboration	0.0744	0.8430***	0.0807	-0.3431**
	(0.0824)	(0.1659)	(0.0942)	(0.1716)
License-To Links (Share in Tech)	0.0003	0.0009	-0.0016	0.0013
	(0.0009)	(0.0010)	(0.0010)	(0.0013)
License-From Links (Share in Tech)	0.0035***	-0.0013	0.0049***	0.0050***
	(0.0007)	(0.0009)	(0.0007)	(0.0007)

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents estimates of the impacts of the regulatory stringency change on firms' network composition. The first part shows the impacts on the geographic composition of firm networks, and the second part shows the impacts on the composition of firm technology networks. All explanatory variables are standardized.

A further breakdown of technological relationships by type in Table 1.9 provides some insight into how firms change their roles in the technology market after experiencing a tightening of regulation. In the first three years of Phase 3, while a one standard deviation increase in $\Delta Stringency_{it}$ leads to an addition of 0.0993 in the number of *License-From* links, where regulated firms license technology from their business partners, it leads to a decrease of 0.1148 in the number of *License-To* links, where they license technology to others. The increase in *License-From* is also significant proportionally. The results on the number of research collaborations are mixed, with a positive coefficient of 0.843 in 2013 but a negative coefficient of -0.3431 in 2015. The rise in *License-From* links in relation to higher $\Delta Stringency_{it}$ could be a result of firms experiencing larger regulation shocks seeking technology solutions to stay compliant in the short run, as innovating by oneself takes time. Given the interconnection of firms through their business network, the negative relationship between *License-To* and $\Delta Stringency_{it}$ could be due to decreased demands from other firms that are also under regulation. The increase in the number of research collaborations with $\Delta Stringency_{it}$ in 2013 might also indicate that firms increase their involvement in developing new technologies to find a longer-term solution.

Overall, the results in Table 1.9 on firms' technological connections suggest that there are potential technology or innovation spillovers through firms' technology networks in the very beginning of Phase 3. The tighter regulation leads to both an increasing number of technology links and turnover of technology relationships, suggesting increasing dynamics of technology networks among firms. Such increased dynamics can create more opportunities for technology and innovation to spill over through interactions between firms. As for potential spillovers accompanied by firms' activities in the technology market, the findings suggest potential spillovers from other firms *to* firms experiencing larger regulation stringency increases in the short run. However, to gain a more holistic understanding of the impacts of regulation on firm innovation activities and related spillovers, further research using patent data or firm R&D expenses is needed.

Table 1.10: Impacts of Regulation Stringency on Firm Network Outcomes

	Early Phase 3 (1)	Year = 2013 (2)	Year = 2014 (3)	Year = 2015 (4)
License-To				
No. of License-To Regulated	-0.0197***	-0.0261**	-0.0332***	-0.0062
	(0.0054)	(0.0103)	(0.0083)	(0.0038)
License-To Regulated (Share in License-To)	-0.1406	-0.3043***	-0.2634**	-0.0302
	(0.0877)	(0.0915)	(0.1197)	(0.0813)
No. of License-To Added	-0.0423***	-0.0329***	-0.0855***	-0.0152***
	(0.0057)	(0.0086)	(0.0123)	(0.0053)
No. of License-To Regulated Added	-0.0049**	-0.0168***	-0.0027	-0.0001
	(0.0022)	(0.0060)	(0.0020)	(0.0017)
No. of License-To Dropped	-0.0224***	-0.0237***	-0.0248***	-0.0200***
	(0.0058)	(0.0074)	(0.0056)	(0.0073)
No. of License-To Regulated Dropped	-0.0023	0.0006	0.0034**	-0.0081**
	(0.0019)	(0.0023)	(0.0015)	(0.0034)
License-From				
No. of License-From Regulated	-0.0027	-0.0043	-0.0035	-0.0013
	(0.0050)	(0.0066)	(0.0056)	(0.0045)
License-From Regulated (Share in License-From)	-0.1483***	-0.0729	-0.0658	-0.0727
	(0.0383)	(0.1000)	(0.1059)	(0.0976)
No. of License-From Added	-0.0128**	-0.0121	-0.0090	-0.0160***
	(0.0056)	(0.0074)	(0.0070)	(0.0060)
No. of License-From Regulated Added	-0.0055***	-0.0121***	-0.0015	-0.0049***
	(0.0013)	(0.0031)	(0.0013)	(0.0017)
No. of License-From Dropped	-0.0044	-0.0118	-1.2×10^{-6}	-0.0036
	(0.0096)	(0.0104)	(0.0099)	(0.0104)
No. of License-From Regulated Dropped	-0.0042***	-0.0074***	-0.0014	-0.0045**
	(0.0016)	(0.0024)	(0.0016)	(0.0019)

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents estimates of the impacts of the regulatory stringency change on firms' technological relationships. The first part shows the impacts on the *License-To* links, and the second part shows the impacts on the *License-From* links. All explanatory variables are standardized.

1.7 Conclusion

In this study, I investigate the complex effects of the EU ETS on firms using a fuzzy RD design that capitalizes on the system's distinct inclusion criteria. The analysis reveals that while regulated firms significantly lowered their direct (Scope 1) emission intensity under the EU ETS, this was paralleled by a marked increase in indirect (Scope 2) emissions. This pattern raises concerns about potential carbon leakage through supply chains, a hypothesis bolstered by a noticeable decrease in the proportion of European suppliers, who are typically subjected to stricter environmental norms. However, the impacts of the EU ETS on firms' technological networks only manifest when the regulation was tightened in the transition to Phase 3. Specifically, an increase in regulatory stringency leads to an expansion of firms' technological networks and an increasing turnover of technological relationships. This increase in dynamics suggests a surge in voluntary technology transfers and potential innovation spillovers in response to tighter regulations. A surprising increase in revenue and net income was found for firms facing tighter regulation. This is likely due to the oversupply of allowances in the earlier years of the EU ETS and the ability of those regulated firms to shift their emissions through supply chains and pass increased costs to their customers thanks to their market power.

This paper extends beyond the traditional scope of analyzing direct impacts of the EU ETS on regulated entities, shedding light on its broader ripple effects, an area not as extensively probed in existing research. These findings carry significant policy implications, emphasizing the importance of a holistic view in the cost-benefit assessment of environmental policies like the EU ETS. The evident risks of carbon leakage and the opportunities for innovation spillovers highlight the need for comprehensive policies that consider wider market dynamics. It is noteworthy, however, that this research primarily focuses on one channel of innovation spillovers and does not account for emissions further along the supply chains (Scope 3 emissions). A more thorough understanding of the EU ETS's impact necessitates the exploration of these aspects. Future research directions include probing additional avenues of innovation spillovers and assessing the long-term viability of firms' responses to environmental regulations.

Chapter 2

Unraveling Price Dispersion in Building Insurance: Evidence from a UK Price Comparison Platform

Abstract

This paper investigates the price dispersion of building insurance policies on a leading price comparison website in the UK. By utilizing real property data and fictitious customer profiles, I collected annual quoted prices and documented two facts: First, substantial price dispersion persists for customers even after controlling for observable policy features. Second, the extent of this dispersion varies significantly across different customers. A simple model suggests that these patterns can be partially explained by customers' preferences for certain providers based on additional features they offer. However, empirical analysis indicates that this explanation is insufficient. Further examination reveals that variations in providers' risk pricing strategies and the use of randomized pricing also contribute to the observed price dispersion.

2.1 Introduction

Since the seminal paper by Stigler (1961), price dispersion in homogeneous goods has attracted significant scholarly attention. Early studies attributed price dispersion primarily to consumer search costs (e.g., Rothschild, 1978; Reinganum, 1979; Carlson and McAfee, 1983). Despite the rise of the internet and price comparison websites (PCWs) reducing search costs, price dispersion persists even on these platforms. Later research (e.g., Varian, 1980; Baye and Morgan, 2001) acknowledged the minimal search costs associated with PCWs but continues to rely on search costs to explain price dispersion, positing that dispersion results from some consumers lacking access to such "information clearinghouses". However, since firms often charge different prices for identical products across various distribution channels and customers shopping through PCWs may inherently differ from those using other channels, search costs may not fully explain the price dispersion observed on PCWs. This suggests the need for alternative explanations beyond traditional search cost theories. This paper examines the price dispersion of home insurance policies on a leading UK PCW. Home insurance is a crucial financial product, closely tied to the property market, which is vital to both consumers and policymakers. The importance of home insurance is heightened by the increasing frequency of extreme weather events globally. Additionally, since prices often indicate market efficiency, understanding the determinants of home insurance prices and their dispersion is essential.

To investigate price dispersion, I collected annual quotes for building insurance policies from *comparethemarket.com*, which compares policies from over 50 providers. I focused on building insurance to simplify data collection and to utilize real property information for data collection. Quoted prices were obtained using recently transacted properties for property inputs and fictitious individuals for personal and household inputs. The use of fictitious individuals enables controlled experiments by varying one input at a time to study its impact on the output variables of interest. Unlike previous audit studies (e.g., Bertrand

and Mullainathan, 2004; Kübler et al., 2018), these quotes were produced by predetermined pricing algorithms, reducing errors and eliminating the need for randomization. To minimize the impact of product differentiation, policies received by each customer were grouped by their most observable features, and price dispersion was measured for each group. Here, a customer is defined as a combination of a real property and a fictitious individual. The data revealed two key findings: First, there is noticeable price dispersion even among seemingly identical policies, with the average residual price—defined as the absolute deviation from the group average—being £84.43, about 21% of the average annual price. Second, the degree of price dispersion varies significantly across customers, with the standard deviation of the group-level standard deviation being £109.68, or 1.23 times the average group-level standard deviation across all groups.

While search frictions are often used to explain price dispersion, they do not appear to play a significant role in this context. Instead, I argue that price dispersion arises from customers valuing additional features offered by insurance providers. A simple framework shows that providers offering valued additional features can charge higher prices for identical policies. If customer preferences for these features are known, providers can price discriminate, charging higher prices to those who value the features more. This framework explains both price dispersion faced by individual customers and the significant differences in price dispersion across customers. To test this, I collected data on insurance providers, classifying them as either non-insurance-focused (NIF) or insurance-focused (IF). NIF providers, with a significant presence in other sectors such as retail, often offer complementary services and can charge higher prices. Empirical evidence supports this hypothesis: NIF providers charge on average £67.37 more annually for seemingly identical policies compared to IF providers. However, the empirical results do not support the hypothesis that providers price discriminate based on self-disclosed customer characteristics. Therefore, while customer preferences can explain the price dispersion faced by a single customer, they cannot account for the significant heterogeneity in price dispersion across customers.

An alternative explanation for the variation in price dispersion across customers is differences in risk pricing. If providers disagree on the risk assessment of the same customer and this disagreement varies across customers, it can lead to the observed patterns. To test this, I examined whether certain customer characteristics predict lower but not zero offer rates. Since providers cannot observe the true risks of customers, they must rely on observable characteristics to estimate risks. When a customer's risk cannot be clearly estimated, providers may exit the market segment due to concerns about adverse selection. If there were no differences in risk pricing, one would expect to see either all providers making offers or none at all to certain customers. However, I found that customers with a history of bankruptcy or recent claims receive fewer but non-zero quotes, suggesting differences in risk pricing across providers. Beyond differences in risk pricing, further investigation reveals that some providers appear to randomize their prices, with the same characteristic sometimes resulting in higher charges and other times in lower charges. This price randomness, possibly as a response to changing market competition, is more likely due to the randomization of markups rather than risk assessments, as risk assessments for a given characteristic should remain stable over short periods. Additionally, I found that a few providers price discriminate based on certain protected characteristics.

Overall, the empirical results suggest that while observed price dispersion can partly be attributed to customers valuing additional provider features, this customer loyalty explanation does not fully account for the considerable differences in price dispersion across customers. Differences in risk pricing and the randomization of markups provide alternative explanations, helping to explain both the price dispersion faced by individual customers and the variation in price dispersion across different customers. Therefore, the existence of price dispersion does not necessarily suggest market inefficiencies. However, with the current data, I cannot rule out the possibility that search frictions also contribute to the observed price dispersion patterns, nor can I disentangle and quantify the proportion of price dispersion due to differences in risk pricing and that due to differences in markups. More data is needed for a further welfare analysis.

This paper contributes to the empirical literature on price dispersion. While most previous studies focus on testing predictions from search models (e.g., Dahlby and West, 1986; Brown and Goolsbee, 2002; Chandra and Tappata, 2011; Allen et al., 2014), this paper explores alternative explanations for price dispersion observed on PCWs, where search frictions play a less significant role. It thus directly contributes to the body of work seeking explanations beyond search frictions (e.g., Carlin, 2009; Woodward and Hall, 2012; Chioveanu and Zhou, 2013). Specifically, it relates to empirical studies on market power and price dispersion, where most existing studies focusing on the airline industry (e.g., Gerardi and Shapiro, 2009; Gaggero and Piga, 2011) and commodity sectors (e.g., Lewis, 2008). Additionally, this study aligns with research on insurance pricing (e.g., Bundorf et al., 2012; Koijen and Yogo, 2015) and with studies using field experiments to identify discrimination in labor or consumer markets (e.g., Ahmed and Hammarstedt, 2009; Edelman et al., 2017; Byrne et al., 2022).

The rest of the paper is structured as follows. Section 2.2 provides institutional background for the UK home insurance market. Section 2.3 explains the data collection methods. Section 2.4 investigates the price dispersion in the data, while Section 2.5 and 2.6 provide explanations for the observed price dispersion patterns. Finally, Section 2.7 conclusions.

2.2 UK Home Insurance Market

Home insurance policies in the UK generally fall into three categories: buildings insurance, contents insurance, and a combination of the two. Buildings insurance, which is the focus of this study, covers damage to the structure, fixtures, and fittings of a property. Contents insurance, on the other hand, covers loss or damage to personal belongings within a property that are not part of the building itself. While there is no legal requirement to purchase home insurance, mortgage providers usually require borrowers to have buildings insurance.

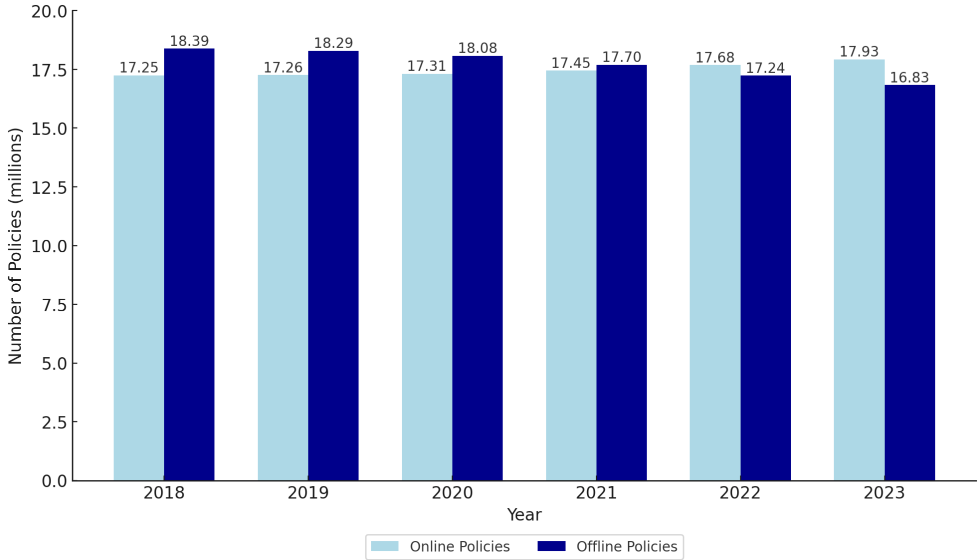
Compared to home insurance markets in other major economies, the UK home insurance market is relatively competitive, with the top five providers accounting for around 30% of market share as of 2022[1]. Major players include companies such as Aviva, Direct Line, and AXA, which dominate market share due to their extensive distribution networks and brand recognition. The majority of UK home insurance customers (around 75%) shop around before buying a policy[2]. Additionally, purchasing home insurance online is becoming increasingly popular in the UK, as shown in Figure 2.1. More than half (51.6%) of people bought their home insurance policy online in 2023. While there is no precise data on the usage of price comparison websites (PCWs), it is reported by the Financial Conduct Authority (FCA) that customers often buy insurance from providers after comparing prices on PCWs.

The retail price of insurance policies is determined by many factors. Broadly speaking, the price from most insurance providers comprises risk-related costs, operational costs, and the margin charged to customers. While the cost component of the price is relatively stable for a given customer, as it primarily depends on the design of the insurance policy and customer risks, the margins can vary substantially due to factors such as distribution channels, market competition, customer characteristics, and even the duration of a customer's relationship with their current insurance provider. The last factor, known as "price walking," refers to the practice of offering new customers low and sometimes ultra-low prices, which increase significantly upon renewal. This practice has been banned by the FCA's General Insurance Pricing Practices (GIPP) since January 2022[3]. Since then, insurance providers are required to charge the same prices for both new and existing customers.

[1]For the home insurance brands dominating the UK market share, see: https://www.consumerintelligence.com

[2]UK Home insurance statistics 2024: https://www.confused.com/home-insurance/home-insurance-statistics

[3]See PS21/11: General insurance pricing practices (GIPP) - amendments from the Financial Conduct Authority (FCA) for details: https://www.fca.org.uk/publications/policy-statements/ps21-11-general-insurance-pricing-practices-amendments



Source: Statista

Figure 2.1: Number of UK Home Insurance Policies Sold by Type (2018-2023)

Generally speaking, there are three types of providers in the UK home insurance market. The first type is insurers who underwrite policies and directly bear the risks associated with them. The second type is intermediaries other than PCWs, which usually do not underwrite the risk but may be involved in pricing since they often design, manufacture, and distribute insurance policies. Both types play important roles in setting prices for insurance policies. While the major income source for insurers is premiums charged for each policy, the core income source for intermediaries is commissions or a portion of the premium. The insurance providers in this study include both insurers and intermediaries, though the latter constitute the majority. The third type is PCWs, which are essentially intermediaries as well. However, instead of participating in the pricing of insurance policies, most PCWs provide platforms to connect insurance providers and customers and earn money through referral fees or cost per acquisition, which may vary by provider and product. The PCW from which this study collected data is an example of such a platform [4]. Therefore, although PCWs do not directly participate in the pricing of insurance policies, they can affect the retail prices

[4]See the description from *comparethemarket.com*: https://www.comparethemarket.com/about-us/

of policies sold on their platforms through the additional referral fees charged to their partners.

2.3 Data

The main dataset used in this study is quoted annual prices for building insurance policies, collected from *comparethemarket.com* using real property information and fictitious individual information as inputs. *comparethemarket.com* is one of the leading UK price comparison websites, initially focused on offering price comparison services for various insurance products, particularly car and home insurance. It has since expanded to include products such as utilities, broadband, and cars. This study focuses exclusively on building insurance to simplify the data collection process. The annual quotes data were collected at two different points in time: August 2020 and March 2024.

2.3.1 Inputs for Data Collection

Similar to most other PCWs, to obtain prices for different building insurance policies, *comparethemarket.com* requires each customer to enter detailed property, individual, and household information and make choices about the policies. Figure B.1.1 provides a screenshot of the beginning of the input page, and Table B.1.1 lists all the questions a customer needs to answer before receiving a list of policies with quoted prices.

To ensure the quotes obtained are as close as possible to what a customer would get in reality, I rely on real properties for the required property-related inputs. Specifically, I obtained a list of recently transacted properties from the UK MH Land Registry Price Paid Data (PPD)[5]. For each property, the PPD data reports its transaction price, transaction date, and most importantly, the detailed address. For this study, I restricted the postcodes to those starting with "BR1,"

[5] PPD data: https://www.gov.uk/government/collections/price-paid-data

which refers to the Bromley district, a town in the southeast of Greater London, to minimize any impact from property location. Given the address of a property, I then searched online to obtain information to answer other required questions. Since these are recent transactions, I could easily find detailed information about these properties on real estate websites such as Rightmove[6]. For instance, I provided answers on the number of rooms a property has based on its actual floor plan. For questions where I could not find answers, I made the best guess based on accessible information.

Unlike the property inputs, which are based on real properties, the inputs for policyholders and their households are fabricated. To simplify data collection and focus on the most relevant characteristics, I keep the answers to some individual-related questions fixed, as shown at the bottom of Table B.1.1. The remaining individual-related questions vary and can be categorized into policyholder-related or household-related questions. For each property, I create a fictitious individual as the baseline and then vary one individual characteristic at a time, so each fictitious individual has a counterpart who differs only in one characteristic. This method allows for counterfactual analysis of the impacts of different individual characteristics on insurance prices. When creating these fictitious individuals, I use a fake identity generator website[7] to generate names, gender, and birthdate. This generator allows me to create names based on race; for example, I can specify that I want an Arabic name, and the website will provide a typical Arabic name. I also double-check the race information embedded in the name using Google search results.

Table 2.1 presents the summary statistics for some continuous input variables. The upper part displays statistics for property-related variables, while the lower part shows statistics for policyholder- and household-related variables. The dataset includes 41 unique property-years and 325 unique policyholders or policyholder-years. Since each property corresponds to multiple fictitious individuals, but not

[6]Rightmove is a UK-based online real estate portal and property website: https://www.rightmove.co.uk/

[7]Website link: https://www.fakenamegenerator.com

the other way around, there are 325 unique customer-years or customers in the sample (as a customer is defined as a combination of a property and an individual). The average purchase price, based on the latest transaction values at the time of data collection, is £504,630, which aligns with the average house price in London in December 2023[8]. The rebuild cost, which measures the cost to completely rebuild a property and typically includes labor and material costs, averages £287,980 in the sample.

Table 2.1: Summary Statistics of Continuous Input Variables

Variables	Count	Mean	SD	Min	Median	Max
Property Variables						
Property Price at Purchase (£000)	41	504.63	379.88	146.00	488.00	1945.00
Number of Rooms	41	6.07	3.56	3.00	4.00	20.00
Rebuild Cost (£000)	41	287.98	141.26	132.00	239.00	700.00
Policyholder Variables						
Age on the Quote Day	325	48.16	15.39	24.00	45.00	82.00
Number of Adults	325	1.82	0.85	1.00	2.00	7.00
Number of Children	325	0.87	0.92	0.00	1.00	4.00
Years Without Claims	325	8.50	1.67	1.00	9.00	9.00

Note: The table presents summary statistics for continuous input variables. The first column, labeled *Count*, represents the number of unique property-years and the number of unique policyholders (also policyholder-years). The property variable *Property Price at Purchase* reflects the most recent real transaction price for a specific property-year. The *Rebuild Cost* is the estimation provided by the Building Cost Information Service (BCIS) as presented on the PCW. *Age on the Quote Day* refers to the age of a fictitious policyholder on the date the data was collected.

The lower part of Table 2.1 and Table 2.2 summarize the fictitious individuals used for data collection. The average age of these individuals is 48.16 years, and the average longest period without claims for these individuals and their families is 8.5 years. Note that in Table 2.2, the proportions of individuals with different characteristics vary significantly. This variation is because I did not randomize based on these characteristics. Although many field experiments using fictitious information randomize based on characteristics of interest, randomization is not necessary for this study for at least two reasons. First, field experiments in previous research often rely on human responses to generate output data, necessitating the randomization of characteristics to avoid bias. However, this is not

[8]See UK House Price Index: December 2023

a concern here, as the outputs are insurance prices determined by pre-specified pricing algorithms. Second, as mentioned above, when collecting data, I ensure that each individual has a counterpart who differs in only one dimension. Since the pairs were collected at the same location and almost simultaneously (only minutes apart), this method is essentially like conducting controlled experiments.

Table 2.2: Summary Statistics of Categorical Input Variables

Variable	Level	Count	Proportion
Gender	Male	140	43.08%
	Female	185	56.92%
Name Implied Race	Asian	98	30.15%
	Black	66	20.31%
	White	116	35.69%
	Arab	18	5.54%
	Other	27	8.31%
Marital Status	Married	169	52.00%
	Single	82	25.23%
	Divorced/Dissolved	55	16.92%
	Widowed/Surviving Civil Partner	19	5.85%
Employment Status	Full-time Employed	159	48.92%
	Part-time Employed	20	6.15%
	Unemployed	9	2.77%
	Self-employed	62	19.08%
	Houseperson	29	8.92%
	Retired	44	13.54%
	Not Employed Due to Disability/Illness	2	0.62%
Ever Declared Bankrupt	No	295	90.77%
	Yes	30	9.23%
Claimed in the Past 5 Years	No	297	91.38%
	Yes	28	8.62%

Besides the property and individual information, customers also need to input their choices on policy features. This includes how much voluntary excess or deductible a customer would like to pay before the policy provider covers the rest of the claim amount. The voluntary excess can be chosen from a drop-down list ranging from £0 to £500 in increments of £50. Furthermore, customers need to specify if they want to include add-ons, which are additional coverage options that may or may not directly relate to the property. The available add-ons are listed at the bottom of the first part of Table B.1.1.

2.3.2 Outputs and Summary Statistics

After providing all the required information, a customer will receive a list of policies with quoted prices from different insurance providers. An example is given in Figure B.1.2. Although this study focuses on the annual price, a customer can choose to pay either annually or monthly. In both cases, the policies are sorted from the lowest to highest price. Key features such as the coverage amount, excesses, and inclusion of add-ons are summarized in an easy-to-read manner for each policy. Most policies include a compulsory excess in addition to the voluntary excess chosen by the customer, so the total excess a customer needs to cover is the sum of these two amounts. More detailed information about each add-on, as shown in Figure B.1.3, can be accessed by clicking the "More details" button.

Using the 325 unique customers, I collected a sample consisting of 13,916 quoted annual prices from 89 unique insurance policies provided by 58 different insurance providers. As shown in Table 2.3, while a majority of 36 providers offer only a single type of policy, 22 providers offer 2 or 3 types of policies. In addition, I collected financial and business data for all providers in the sample and categorized them as IF or NIF based on whether they are pure players in the insurance sector or not. The last two columns in Table 2.3 show the counts for NIF and IF providers, respectively. Most providers in the sample are pure players in the insurance sector. Only 15, or 25.86%, of providers are NIF providers, which are best recognized in sectors other than insurance.

Table 2.3: Overview of Insurance Providers and Policies

Variables	Total	Non-Insurance-Focused (NIF)	Insurance-Focused (IF)
Number of insurance policy	89	25 (28.09%)	64 (71.91%)
Number of insurance provider	58	15 (25.86%)	43 (74.14%)
Number of providers with 1 policy	36	8	28
Number of providers with 2 policies	13	4	9
Number of providers with 3 policies	9	3	6

Table 2.4 presents the summary statistics for quoted annual prices in GBP. The

average price of a building insurance policy in this sample is £421.55, with a significant standard deviation of £263.28, which is more than half of the average price. Furthermore, the average price charged by NIF providers is £474.74, nearly £70 more than that of IF providers. The second and last parts of Table 2.4 provide summary statistics at the customer level and policy level, respectively. The number of policies obtained by a customer averages 42.82, but ranges widely from a minimum of 6 policies to a maximum of 70 policies. The average of the average prices faced by a customer is £394.44, which differs from the mean annual price across the sample due to the varying number of policies across customers. Moreover, there is noticeable price dispersion for each customer, and this dispersion varies considerably across customers. Specifically, the average price dispersion, measured by the standard deviation (SD), is £148.11, and the SD of the SD itself is £96.12, more than half of the mean. I also measure price dispersion using the coefficient of variation (CV) following Baye et al. (2006) and within-customer price range. Both measures lead to similar conclusions.

Table 2.4: Summary Statistics for Quoted Annual Prices

Variables	Count	Mean	SD	Min	Median	Max
Across the Sample						
Annual Price (All Providers)	13916	421.55	263.28	67.31	347.03	7016.69
Annual Price (NIF Providers)	3377	473.74	281.30	76.75	394.77	2558.29
Annual Price (IF Providers)	10539	404.83	255.00	67.31	332.87	7016.69
Customer-level Variables						
Number of Policy	325	42.82	15.91	6.00	39.00	70.00
Average Annual Price (μ_i)	325	394.44	181.25	120.82	361.29	1159.72
SD OF Annual Price (σ_i)	325	148.11	96.12	27.94	139.04	968.70
CV of Annual Price (σ_i/μ_i)	325	0.36	0.11	0.14	0.35	0.99
Range of Annual Price	325	670.65	546.14	77.50	534.79	6651.57
Policy-level Variables						
Policy Offer	89	0.48	0.28	0.00	0.41	1.00
Average Annual Price (μ_p)	89	432.63	152.06	179.38	418.02	1261.17
SD OF Annual Price (σ_p)	89	207.56	102.87	21.76	201.93	580.63
CV of Annual Price (σ_p/μ_p)	89	0.47	0.16	0.12	0.45	1.10
Range of Annual Price	89	1081.79	878.06	0.00	934.91	6757.42

Note: The table presents summary statistics for quoted annual prices. The first part shows summary statistics for the entire sample and by provider type. The second part focuses on customer-level variables, and the last part on policy-level variables. SD stands for standard deviation and CV for coefficient of variation.

At the policy level, the average offer rate across the 89 different types of policies is 0.48, with a standard deviation of 0.28, indicating considerable variation. While some policies are offered to all 325 customers, others are barely offered to any. Again, there is considerable price dispersion within each policy, and this dispersion varies significantly across different policies. This is not surprising, as the former reflects customer differences, and the latter includes policy differences or product differentiation.

2.4 Identify Residual Price Dispersion

While the summary statistics in Table 2.4 show considerable price dispersion faced by customers, and that this dispersion varies widely across customers, these findings are not surprising due to unaccounted product differentiation and variations among customers. Therefore, to make the discussion of price dispersion meaningful, comparisons must be made on a like-for-like basis. To achieve this, I first match quotes by their data collection date, customer, policy choices, and the most observable policy features, retaining only observations with at least one match. This approach allows for comparisons of quotes from seemingly identical policies obtained on the same date with specific customer input sets. While some hidden differences among policies within a group may persist, this method addresses the most significant product differentiation. Customers would otherwise need to read extensive documentation from different providers, assuming such documents are easily accessible. I then define the residual price for each policy p as the absolute deviation of its annual price from the average price of the matched group, given by:

$$Residual.Price_p = |Price_{iph} - \frac{1}{N_G} \sum_{p \in \mathbf{G}} Price_{iph}|$$

where G denotes a matched group and N_G the number of policies in the group.

Table 2.5 presents the summary statistics derived from the matched samples, comprising 8,327 observations with at least one match. Significant dispersion in residual prices remains, with an average residual price of £84.43 and a standard deviation of £106.34. The minimum and maximum residual prices are £0.02 and £1,218.75, respectively. These results suggest that even after controlling for obvious differences, customers still face different prices for seemingly identical policies, and the level of price dispersion varies starkly across matched groups. The second half of Table 2.5 shows statistics at the matched group level, where each group has an average of 3.64 policies. Within-group price dispersion, measured by both SD and CV, remains notable. The average SD across all matched groups is £88.88, and the average CV is 0.21, meaning the SD is, on average, 21% of the group mean. The large SDs of both group-level SD and group-level CV compared to their means suggest significant variation in price dispersion across groups. Additionally, I measured price dispersion using residuals from multiple fixed effects. The results, shown in Table B.2.1 and visualized in Figure B.2.1, are consistent with those derived from the matching method.

Table 2.5: Summary Statistics for Residual Prices and Prices of Matched Groups

Variables	Count	Mean	SD	Min	Median	Max
Group of policies by date, property, individual, policy choices and features						
Observation-Level						
Residual Price	8327	84.43	106.34	0.02	46.83	1218.75
Group-Level						
Number of Policies	2286	3.64	2.26	2.00	3.00	18.00
Average Annual Price (μ_g)	2286	402.76	216.73	70.62	343.75	2169.35
SD of Annual Price (σ_g)	2286	88.88	109.68	0.04	52.12	1590.42
CV of Annual Price (σ_g/μ_g)	2286	0.21	0.17	0.00	0.17	0.98
Range of Annual Price	2286	185.01	233.53	0.05	97.40	2249.20

Note: The table shows summary statistics after matching observations by date, customer (property + individual), policy choices, and observable features, retaining only those with at least one match. This ensures each group has at least two observations. The residual price is defined as the absolute deviation of an observation's annual price from the group mean.

As a visualization of the group-level price dispersion, Figure 2.2 plots the standard deviation of annual prices against the average annual price for each matched group. While a few matched groups exhibit zero price dispersion, most still experience non-zero, and in some cases, significant price dispersion. Additionally, for each value of average annual price, there is noticeable variation in the price dispersion. Overall, the statistics in this section document two key findings:

First, considerable price dispersion exists for a customer even when observable product differentiation is controlled for. Second, the level of price dispersion varies significantly across matched groups. The next two sections will attempt to explain the observed price dispersion patterns.

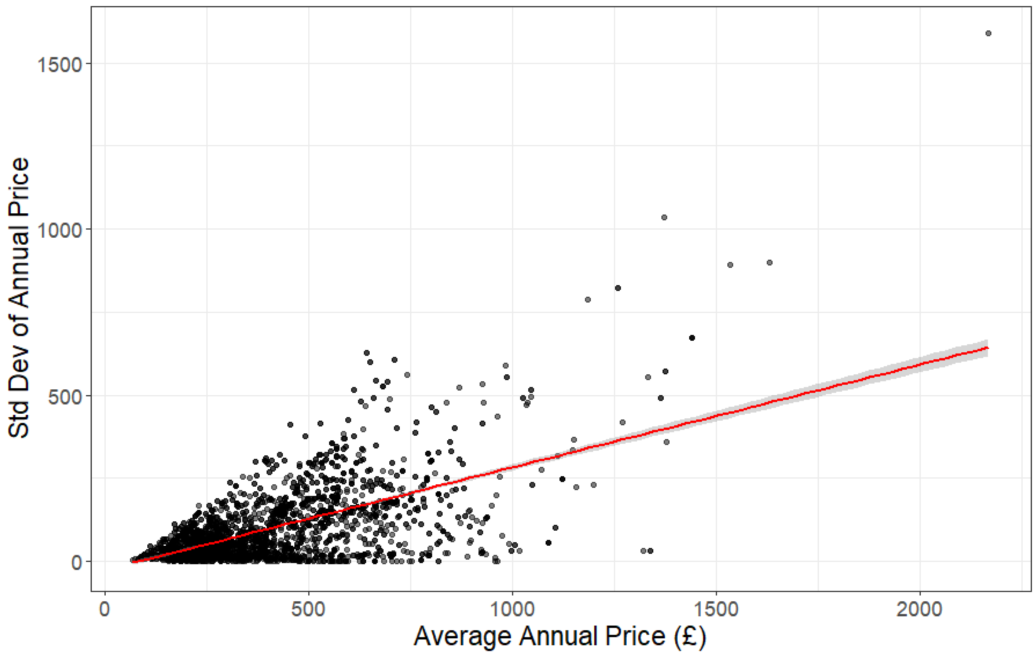


Figure 2.2: Group-level Price Dispersion and Average Annual Price

Note: The figure plots group-level price dispersion, measured as the standard deviation of annual prices, against the group average annual price. Each black dot represents one of the 2,286 matched groups. The red line is the best-fit line.

2.5 Market Power from Customer Preferences

In a perfectly competitive home insurance market without any frictions, homogeneous insurance policies should charge the same price for the same customer. However, as the statistics in the last section show, price dispersion exists even for seemingly homogeneous policies in practice. One explanation, as argued by Stigler (1961), is that there are no absolutely homogeneous products. Even identical insurance policies can be perceived differently by customers if they are sold by providers with distinct features that customers also value. For instance, a customer may prefer a policy from one provider over another due to complementary products or services offered by that provider. If a provider offers certain features that are highly valued by some customers, then that insurance provider will have a relatively loyal customer base and can therefore charge higher prices.

2.5.1 Conceptual Framework

Consider a simple framework where two *different* providers sell buildings insurance policies that are identical in terms of policy features, terms, and conditions. The marginal cost of providing the policy for provider $j \in \{A, B\}$ is c_j. There are two types of customers $i \in \{1, 2\}$, who are identical in all aspects except for their preference towards providers. The willingness to pay (WTP) of type i customers to provider j is $\nu_{ij} = \overline{\nu} + \mu_{ij}$, where $\overline{\nu} > c_j$. Specifically, type 1 customers attach an additional value $\mu_{1A} = \nu_A$ to provider A but nothing to provider B, i.e., $\mu_{1B} = 0$. Type 2 customers do not attach additional values to any providers, so $\mu_{2j} = 0$ for both A and B. Customers choose which provider to buy from to maximize their utility $U_i(j) = \nu_{ij} - p_{ij}$, where p_{ij} is the price charged by provider j and it may vary with customer type. If purchasing from either provider generates the same utility, a customer will randomly choose one to buy from. Providers follow Bertrand competition and set prices to maximize their total profits.

A. Pricing With Observable Customer Preferences

If insurance providers know the preferences of each type of customer, they will compete in market segments divided by customer types and set optimal prices by solving the following problem:

$$\max_{p_{ij}} \pi_{ij} = p_{ij} - c_j$$
$$s.t. \quad U_i(j) \geq 0; \ \pi_{ij} \geq 0$$
$$U_i(j) \geq U_i(-j)$$

For provider A, this implies that $c_A \leq p_{1A} \leq p_{1B} + \nu_A$ for price on type 1 customers, and $c_A \leq p_{2A} \leq p_{2B}$ for price on type 2 customers. For provider B, this implies that $c_B \leq p_{1B} \leq p_{1A} - \nu_A$ for price on type 1 customers, and $c_B \leq p_{2B} \leq p_{2A}$ for price on type 2 customers. It is straightforward to show that the results depend on the relative marginal costs of the two providers. Specifically, if $c_A < c_B$, provider A has a cost advantage over provider B and can thus always outcompete provider B and attract all customers in both market segments by charging a price $p_{iA} = c_B - \delta$. However, since type 1 customers attach an additional value ν_A to provider A, provider A can increase the price by ν_A and still attract all type 1 customers. Therefore, provider A will set $p_{1A} = c_B + \nu_A - \delta$ and $p_{2A} = c_B - \delta$ and attract all customers, with both types of customers receiving $U_i = \overline{\nu} - c_B + \delta$. However, if $c_A > c_B$, whether provider B can attract both types of customers depends on how large a cost advantage provider B has. If provider B has a large cost advantage such that $c_B + \nu_A \leq c_A$, then it can charge $p_{1B} = c_A - \nu_A - \delta$ for type 1 customers and $p_{2B} = c_A - \delta$ for type 2 customers, outcompeting provider A in both market segments. In this case, both type 1 and type 2 customers purchase from provider B, receiving utility $U_1 = \overline{\nu} + \nu_A - c_A + \delta$ and $U_2 = \overline{\nu} - c_A + \delta$, respectively. If the costs are equal, provider A charges $p_{1A} = c_A$ and provider B charges $p_{1B} = c_A - \nu_A$, with type 1 customers randomly choosing between the two providers and receiving $U_1 = \overline{\nu} + \nu_A - c_A$. On the other hand, if provider B has a relatively small cost advantage such that $c_B \leq c_A < c_B + \nu_A$, it cannot undercut provider A to attract type 1 customers without making a loss, but it can still charge $p_{2B} = c_A - \delta$ to attract type 2 customers. In this case, type 1 customers will buy from provider A at a price of $p_{1A} = c_B + \nu_A - \delta$ and receive utility $U_1 = \overline{\nu} - c_B + \delta$, while type 2 customers will buy from provider B at a price of $p_{2B} = c_A - \delta$ and receive $U_2 = \overline{\nu} - c_A + \delta$. When $c_A = c_B$, $p_{2A} = p_{2B} = c_j$ and the two providers split the market for type 2 customers equally. Table B.3.1 in Appendix B.3 summarizes the results by different relative costs between the two providers. In all cases, provider A is able to charge higher prices than provider B for type 1 customers.

B. Pricing With Unobservable Customer Preferences

If insurance providers do not know customer preferences, they cannot price discriminate based on customer types. Instead, they will set a single price to maximize aggregated profits from both market segments. In this case, the results will depend on both market size and the relative marginal costs of the two providers. Assume that the number of type 1 customers is N_1 and the number of type 2 customers is N_2. Providers now set a price to maximize $\pi_j = N(p_j)(p_j - c_j)$ subject to similar conditions as in the previous case. Here, $N(p_j)$ denotes the number of customers as a function of price.

<u>**Case 1**</u> If provider A has a cost advantage over provider B such that $c_A \leq c_B$[9], then for any $c_B \leq p_B \leq \overline{\nu}$, provider A can always charge $p_A = p_B - \delta$ and get both types of customers, or it can charge a higher price $p_A = p_B + \nu_A - \delta$ and only attract type 1 customers. Provider A will choose to focus on type 1 customers if the total profit from that market segment is larger than the total profit from both market segments. That is, if

$$\begin{aligned} N_1(p_B + \nu_A - \delta - c_A) &> (N_1 + N_2)(p_B - \delta - c_A) \\ \text{or} \quad p_B &< \frac{N_1 \nu_A}{N_2} + c_A + \delta \end{aligned} \tag{2.1}$$

If $c_B \leq \frac{N_1\nu_A}{N_2} + c_A + \delta \leq \overline{\nu}$, to incentivize provider A to compete only for type 1 customers, provider B can set $p_B = \frac{N_1\nu_A}{N_2} + c_A$ to maximize its profit in the market segment for type 2 customers. In this case, provider A will set price $p_A = \frac{N_1\nu_A}{N_2} + c_A + \nu_A - \delta$ to attract only type 1 customers. Note, this requires that $c_B - c_A - \delta \leq \frac{N_1\nu_A}{N_2}$ or $N_2(c_B - c_A - \delta) \leq N_1\nu_A$. That is, the additional gains from focusing on the type 1 customer market should be at least the same as the minimum amount lost due to giving up the type 2 customer market; otherwise, provider B cannot find a sufficiently low price to urge provider A to focus only on the market for type 1 customers without suffering a loss. If $\frac{N_1\nu_A}{N_2} + c_A + \delta > \overline{\nu}$,

[9] It can be shown that when $c_A = c_B$, the conclusion is the same for $p_B > c_B$. For $p_B = c_B$, provider A will choose to focus only on the type 1 customer market.

any $p_B \leq \overline{\nu}$ will give provider A the incentive to focus on the type 1 customer market. In this case, provider B sets $p_B = \overline{\nu}$ to maximize its profit in the type 2 customer market and provider A sets $p_A = \overline{\nu} + \nu_A - \delta$ to maximize its profit in the type 1 customer market. The two providers are essentially monopolists in each market segment. If $\frac{N_1 \nu_A}{N_2} + c_A + \delta < c_B$, provider B cannot break even at any prices that incentivize provider A to focus only on the type 1 customer market, and thus will eventually go out of business[10].

<u>**Case 2**</u> If provider B has a sufficiently large cost advantage over provider A such that $c_A \geq c_B + \nu_A$, then for any $c_A \leq p_A \leq \overline{\nu} + \nu_A$, B can always undercut A by charging $p_B = p_A - \nu_A - \delta$ and get both types of customers, or charge $p_B = \min\{p_A - \delta, \overline{\nu}\}$ and only get type 2 customers. Provider B will choose the latter if:

$$N_2(min\{p_A - \delta, \overline{\nu}\} - c_B) > (N_1 + N_2)(p_A - \nu_A - \delta - c_B)$$

If $c_A \leq p_A \leq \overline{\nu}$, the above condition becomes:

$$N_2 \nu_A > N_1(p_A - \nu_A - \delta - c_B) \quad \text{or} \quad p_A < \frac{N_2 \nu_A}{N_1} + \nu_A + c_B + \delta \tag{2.2}$$

Intuitively, if provider A sets a sufficiently low price such that for provider B, the value lost from charging a lower price to existing type 2 customers is larger than the value gained from acquiring type 1 customers, then provider B would not want to compete for both types of customers. Furthermore, if $c_A \leq \frac{N_2 \nu_A}{N_1} + \nu_A + c_B \leq \overline{\nu}$, then provider A charges $p_A = \frac{N_2 \nu_A}{N_1} + \nu_A + c_B$ to maximize profit and attract type 1 customers, while provider B charges $p_B = \frac{N_2 \nu_A}{N_1} + \nu_A + c_B - \delta$ and attracts only type 2 customers. However, if $\frac{N_2 \nu_A}{N_1} + \nu_A + c_B > \overline{\nu}$, or $\nu_A > \frac{N_1}{N_1 + N_2}(\overline{\nu} - c_B)$, p_A

[10] Note, if we assume Bertrand competition, B has the incentive to lower its price to compete with A in the type 1 customer market. This will lead to $p_B = c_B$ and $p_A = c_B + \nu_A - \delta$. B still only gets type 2 customers while A gets type 1 customers. However, if we assume that over time each provider can learn the cost of their opponent, then B knows that there is no point in competing for the type 1 customer market. In this case, B will stick to the upper boundary in Equation (2.1).

must satisfy the following condition instead:

$$
\begin{aligned}
N_2(\overline{\nu} - c_B) &> (N_1 + N_2)(p_A - \nu_A - \delta - c_B) \\
\text{or} \quad p_A &< \frac{N_2}{N_1 + N_2}(\overline{\nu} - c_B) + \nu_A + c_B + \delta
\end{aligned} \tag{2.3}
$$

Since $\overline{\nu} < p_A \leq \overline{\nu} + \nu_A$ must hold, it implies that as long as the number of type 1 customers is sufficiently small such that $0 < \nu_A - \frac{N_1}{N_1+N_2}(\overline{\nu} - c_B) + \delta \leq \nu_A$[11], provider A will charge $p_A = \frac{N_2}{N_1+N_2}(\overline{\nu} - c_B) + \nu_A + c_B$ and get all type 1 customers, and provider B will charge $p_B = \overline{\nu}$ and attract all type 2 customers. Again, if $\frac{N_2 \nu_A}{N_1} + \nu_A + c_B + \delta < c_A$, A cannot prevent B from taking both markets[12].

<u>Case 3</u> If provider B has a relatively small cost advantage such that $c_B < c_A < c_B + \nu_A$, neither provider can acquire both markets if they intend to compete for both. Furthermore, it can be shown that there does not exist an equilibrium where neither provider wants to deviate. In other words, both providers will constantly adjust their prices. To see this, start with $p_B^0 = p$, where $c_B \leq p < \frac{N_1 \nu_A}{N_2} + c_A + \delta$, so that (2.1) is satisfied and provider A only wants to target type 1 customers. Given $p_B^0 = p$, the profit-maximizing price for A is $p_A^0 = p + \nu_A - \delta$. If p_A^0 violates (2.2) or (2.3), B will want to compete for both types of customers. In this case, B will charge $p_B^1 = p_A^0 - \nu_A - \delta = p - 2\delta$ to try to get type 1 customers from A. As p_B^1 still satisfies (2.1), provider A will only compete for type 1 customers, lowering its price to $p_A^1 = p + \nu_A - 3\delta$. If p_A^1 is still too high so that (2.2) or (2.3) is violated, this process will continue until $p_A^i = p_B^i + \nu_A - \delta$ satisfies (2.2) or (2.3), in which case provider B no longer wants to acquire both markets but only targets type 2 customers. Given B only wants to acquire type 2 customers, it can increase its price from p_B^i to $p_B^{i+1} = p_A^i - \delta$ to maximize profit while still attracting type 2 customers. If p_B^{i+1} violates (2.1), A will compete for both types again by lowering its price p_A^i further. B will then respond by also lowering its price p_B^{i+1}. This price

[11] Given $c_A \geq c_B + \nu_A$ and $\overline{\nu} > c_A$, $\overline{\nu} > c_B + \nu_A$ or $\overline{\nu} - c_B > \nu_A$ must hold.

[12] Similarly, if p_A violates Equation (2.3), B will also compete for type 1 customers with A, and eventually Equation (2.3) holds again. On the other hand, in a Bertrand competition, A might lower prices to compete for type 2 customers until $p_A = c_A$ and $p_B = c_A - \delta$. However, A still only gets type 1 customers, and B gets type 2 customers. If costs can be learned over time, then A will stick to the largest possible price allowed by Equation (2.3).

competition continues until B's price satisfies (2.1) again, in which case A only wants to acquire type 1 customers. However, to maximize its profit in the type 1 customer market, A will increase its price so that $p_A = p_B + \nu_A - \delta$. If the resulting p_A satisfies (2.2) or (2.3) so that B focuses on the type 2 customer market, B will have the incentive to increase its price to just below A's to maximize its profit, i.e., $p_B = p_A - \delta$. This continues until the price gets too high and one of the providers wants to compete for both types again, starting the downward spiraling of prices. In sum, as long as one of the providers wants to acquire both types of customers, there will be a price war where both providers lower their prices until the price is sufficiently low for each to specialize in only one market segment. However, once they specialize in their own market, they have the incentive to maximize profits by increasing prices to the level that is just low enough to keep their customers in their specialized market segment. As the increase of price is benchmarked at the opponent's price, this will lead to an upward spiraling of prices. At some point, the price gets too high and one of the providers wants to compete for both types again, starting the downward spiraling of prices.

2.5.2 Hypotheses

As demonstrated by the simple framework above, under either observable or unobservable customer preferences, provider A can charge a higher price for the same insurance policy than provider B, as long as the marginal cost of provider A is not too high. This holds even in the dynamic case with unobservable customer preferences, where both providers constantly adjust their prices. Intuitively, if an insurance provider offers additional features valued by some customers, it can incorporate the value of these features into the price, resulting in a higher charge for the same policy. Furthermore, if customer preferences for these additional features can be observed, insurance providers can price discriminate based on these preferences, charging higher prices to customers who place greater value on the additional features.

This framework offers a potential explanation for the existence of price dispersion faced by individuals and the heterogeneity of price dispersion across individuals. To test this, ideally, one would need to observe all features from different insurance providers and determine which features are valued by customers. This is challenging, if not impossible, in practice. To address this obstacle, I collected detailed data on each insurance provider, allowing me to distinguish between providers who are pure players in the insurance market and those who also operate in other non-insurance sectors. Non-insurance-focused (NIF) providers typically have a significant presence in sectors beyond insurance, such as big supermarket firms like Tesco and Sainsbury's or financial service providers like retail and commercial banks. Conversely, insurance-focused (IF) providers are pure players, focusing solely on insurance, though not exclusively on home insurance. Compared to pure players, NIF providers offer additional services that can complement their home insurance policies, leading to a higher valuation from some customers. For instance, insurance products sold by Sainsbury's Bank can benefit from its loyalty card scheme used by its grocery shoppers. Thus, NIF providers are more likely to charge higher prices, all else being equal.

> **Hypothesis 1** *For the same (or seemingly the same) insurance policy, insurance providers who also operate in other non-insurance sectors (NIF providers) will charge higher prices than providers who are pure players.*

For heterogeneity in price dispersion to exist, the framework suggests that there must be price discrimination based on customer preferences. As shown in Table B.3.1, if insurance providers can identify customer preferences, they will charge higher prices only to customers who attach higher value to their additional features. In this case, customers with different preferences will face different levels of price dispersion. Those who value different providers similarly will face lower price dispersion, while those who value different providers differently will face higher price dispersion. Since customer preferences cannot be directly observed, insurance providers can only estimate these preferences based on other observable personal characteristics. Although insurance providers may obtain additional data on customers from other sources in reality, this is not possible here due to the fictitious nature of individuals used in this study. Therefore, if the differences in price dispersion across individuals are due to price discrimination based on customer preferences, then insurance providers must be using self-disclosed characteristics to infer these preferences. This leads to the second hypothesis:

> **Hypothesis 2** *If insurance providers can infer customer preferences from their self-disclosed characteristics, then the price differences charged by NIF providers and pure-player providers should vary with customer characteristics.*

2.5.3 Empirical Results

To test Hypothesis 1, I first match quotes by data collection date, property, individual, and observed policy features. This allows me to compare seemingly identical policies obtained using specific property-individual inputs. In the baseline regression, I simply regress the quoted annual price on an indicator that equals 1 if the provider is a NIF provider, controlling for matched group fixed effects. However, apart from additional services from providers, customers may also be willing to pay higher prices for policies from providers with higher reputations due to information asymmetry. To control for this, I also search on major review websites such as *Which?*[13] and add a dummy variable *Received Top Reviews* to indicate whether an insurance provider has received top reviews in recent years. The results are shown in Table 2.6. Among all matched groups, only those with both NIF and IF providers and with both top-reviewed and not top-reviewed providers are included.

It is clear that NIF providers charge significantly higher prices. Column (1) in Table 2.6 suggests that for a very similar insurance policy, NIF providers charge an average of £79.46 more annually. The average annual price difference increases

[13] See: https://www.which.co.uk/

to £96.37 and remains statistically significant after controlling for provider reputation, as shown in column (2). In column (3), I also include the log of total assets of providers to account for the possibility that larger firms might enjoy greater recognition from customers, and the result still holds. To further eliminate product differentiation, I repeat the analyses for a subset of quotes on insurance policies without any add-ons. The results, shown in columns (4) to (6), indicate that the price differences remain significant and are even enlarged.

Table 2.6: Quoted Annual Price by Provider Type

Dependent Variable:	Annual Price					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Non-Insurance Focus	79.46***	96.37***	67.37***	78.73***	104.4***	90.14***
	(9.039)	(9.169)	(8.371)	(16.01)	(16.00)	(15.37)
Received Top Reviews		63.71***	39.80***		78.05***	66.41***
		(6.942)	(7.505)		(16.32)	(15.02)
ln Total Asset (£M)			11.07***			10.43**
			(1.517)			(4.593)
Fixed-effects						
Matched Group	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,885	3,885	3,885	923	923	923
R^2	0.65497	0.66592	0.67488	0.58815	0.60296	0.60978
Within R^2	0.04216	0.07257	0.09744	0.03686	0.07148	0.08745

Clustered (group_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

If customer preferences for additional provider features are the sole explanation for price dispersion across customers, then the observed differences in price dispersion across customers indicate that insurance providers can infer customer preferences from their self-disclosed characteristics and charge prices accordingly, as stated in Hypothesis 2 above. To test this hypothesis, I run the following regression for different customer features:

$$\begin{aligned} Annual.Price_{ig} = {} & \delta_g + \beta_1 Non\text{-}Insurance\text{-}Focused_{ig} + \beta_1 Customer.Feature_{ig} \\ & + \beta_3 Non\text{-}Insurance\text{-}Focused_{ig} \times Customer.Feature_{ig} \\ & + \theta X_{ig} + \epsilon_{ig} \end{aligned}$$

Each observation here is the quoted annual price for a specific customer (i.e., a property-individual combination) from a particular insurance provider. Quotes are matched by data collection date, property, observable policy features, and all other customer characteristics except for the one under investigation. For instance, if gender is the characteristic of interest, then quotes are matched by date, property, observable policy features, and all customer characteristics other than gender. In each matched group, quotes are obtained for a fictitious individual and his/her counterpart, with the only difference between the two being the characteristic of interest. This setup creates an ideal environment for counterfactual analysis. As in the previous test, only groups with both NIF and IF providers and top-reviewed and not top-reviewed providers are included. δ_g captures the matched group fixed effects. $Non\text{-}Insurance\text{-}Focused$ indicates whether the quote is from a provider with significant presence in sectors other than insurance. $Customer.Feature$ is a categorical variable capturing the specific customer characteristics of interest, and the third term is the interaction between the first two terms. X_{ig} includes other controls. If NIF providers can identify customer preferences through their self-disclosed characteristics, they will charge higher prices to customers who value the additional services they provide based on certain characteristics. Thus, the coefficient β_3 of the interaction term should be significant for some customer characteristics.

Table 2.7 presents the results for personal characteristics tied to the policyholder, who in this case is the fictitious individual requesting quotes through the price comparison website. The coefficients on the interaction term for the five personal characteristics—gender, non-white/white, not working/working, and age—are insignificant, suggesting that the higher prices charged by NIF providers do not vary with these personal characteristics. However, a further breakdown of race, marital status, and employment status in Table B.3.2 shows some price discrimination for certain races and employment statuses. Specifically, while NIF providers generally charge higher prices, the higher prices are mainly charged to individuals with white-sounding and Asian-sounding names. Individuals with Arab-sounding names are charged significantly lower prices. Regarding employment status, NIF providers charge significantly higher prices for individuals who are unemployed.

Table 2.7: Results by Provider Type and Policyholder Characteristics

Dependent Variable:	Annual Price				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Non-Insurance Focus	85.96*	86.83	32.00	86.62**	42.19
	(43.31)	(65.26)	(55.74)	(37.19)	(64.62)
Non-Insurance Focus × Gender (Female)	-3.532				
	(30.75)				
Non-Insurance Focus × Race (Non-White)		-2.225			
		(2.359)			
Non-Insurance Focus × Not Married			-15.18		
			(12.33)		
Non-Insurance Focus × Not Working				21.84	
				(22.93)	
Age by Pricing Date × Non-Insurance Focus					0.4122
					(1.284)
Gender (Female)	8.469				
	(8.269)				
Race (Non-White)		2.225			
		(2.359)			
Not Married			14.31		
			(9.761)		
Not Working				30.17***	
				(6.396)	
Age by Pricing Date					-2.284***
					(0.5675)
Received Top Reviews	43.64	47.93	178.6***	50.78**	78.36***
	(37.58)	(78.90)	(24.12)	(24.78)	(23.41)
In Total Asset (£M)	12.95*	10.66	2.497	13.90*	9.994*
	(7.346)	(19.09)	(8.789)	(7.240)	(5.449)
Fixed-effects					
Matched Group	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	315	92	192	572	641
R^2	0.40454	0.17233	0.41278	0.58338	0.63903
Within R^2	0.12959	0.08616	0.27757	0.13984	0.14694

Clustered (Matched Group) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The results for customer characteristics associated with the policyholder's household are shown in Table 2.8. Unlike policyholder characteristics, most household characteristics affect the quoted annual insurance prices from both IF and NIF providers. However, these household characteristics are more likely to reflect the risks of a specific customer. In this case, the significant coefficients on the interaction terms simply indicate that NIF providers use these household characteristics for risk-pricing. This is further supported by the fact that the coefficients on $Customer.Features_i$, which capture the relationships between household characteristics and the prices from IF providers, are also mostly significant. This suggests that both types of providers use household characteristics in insurance pricing. However, with the current data, it is impossible to completely disentangle the effects of risk pricing from preference-based markups in the quoted annual price.

Table 2.8: Results by Provider Type and Household Characteristics

Dependent Variable:	Annual Price					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Non-Insurance Focus	-107.4	115.3***	161.1***	65.60**	67.84***	9.843
	(104.1)	(37.98)	(50.85)	(27.49)	(24.46)	(23.89)
No. of Adults × Non-Insurance Focus	41.22					
	(39.63)					
No. of Children × Non-Insurance Focus		-56.63**				
		(25.63)				
Years No Claims × Non-Insurance Focus			-4.914			
			(4.312)			
Non-Insurance Focus × Mortgaged				-59.94*		
				(34.94)		
Non-Insurance Focus × Ever Declared Bankrupt					-76.87*	
					(38.87)	
Non-Insurance Focus × Claimed in Past 5 Years						104.3**
						(39.07)
No. of Adults	12.66*					
	(5.108)					
No. of Children		25.58**				
		(9.814)				
Years No Claims			-2.379			
			(1.591)			
Mortgaged				25.58***		
				(8.386)		
Ever Declared Bankrupt					54.75**	
					(20.29)	
Claimed in Past 5 Years						63.12***
						(13.32)
Received Top Reviews	-16.76	80.40**	79.05***	79.81**	-19.53	-29.80
	(86.76)	(30.89)	(21.95)	(35.40)	(23.36)	(26.49)
In Total Asset (£M)	6.018	7.970	6.634	18.18***	2.157	13.43
	(33.15)	(7.729)	(6.741)	(6.432)	(7.341)	(8.166)
Fixed-effects						
Matched Group	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	52	256	484	651	239	357
R^2	0.17111	0.63985	0.70153	0.75854	0.52021	0.56972
Within R^2	0.01360	0.14024	0.18498	0.11927	0.05877	0.19077

Clustered (Matched Group) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Overall, the results show that price dispersion faced by a customer can be partially attributed to customers valuing additional services provided by some insurers, allowing these insurers to charge higher prices. This is essentially unobserved product differentiation. However, this does not fully explain the significant differences in price dispersion across different customers. Although NIF providers price discriminate based on household characteristics, as shown in Table 2.8, these characteristics are likely used, at least partially, for risk pricing rather than preference-based price discrimination. Consequently, the significant differences in price dispersion across customers might be due to differences in risk pricing from different providers varying with customer characteristics. While it is not possible to disentangle these factors with the current data, it is clear that significant differences in price dispersion across customers require that the price disagreement among different providers must vary across customers.

2.6 Alternative Explanations

To understand the origin of price disagreement, ideally one would like to know how insurance providers price policies. While the exact pricing function of each provider is unknown, the FCA (2019) survey on major general insurance providers indicates that a typical profit-maximizing insurance provider sets prices to maximize the difference between expected future income from a customer and the expected costs, which include both expected claims costs associated with risks and the provider's operational costs. This implies that the price charged by insurance providers includes not just the expected costs for insuring a customer but also a margin that might depend on certain characteristics of the customer correlated with their willingness to pay. Conceptually, the quoted price for an insurance policy p can be written as:

$$Price_{ip} = E[Cost_{ip}|WTP_{ip} \geq Price_{ip}] + Markup_{ip} \tag{2.4}$$

The disagreement on prices for a customer is either due to disagreement on risk pricing (the first part of Equation (2.4)) or disagreement on the margins charged to the customer (the second part of Equation (2.4)). Since it is difficult to fully disentangle risk pricing and margins in any quoted annual prices, this section will provide alternative explanations with suggestive evidence.

2.6.1 Differences in Risk Pricing

If different providers price the risk of the same customer differently, and these differences in risk pricing vary across customers, this can lead to both price dispersion faced by an individual customer and differences in price dispersion across customers. Since it is impossible to quantify the portion of price dispersion due to risk pricing with the current data, I will only test whether there are any differences in risk pricing among different providers.

Insurance providers may price risks differently because they cannot observe the true risks of their customers. Instead, they estimate customer risks using potentially different variables and models. The question is how and why the disagreement in risk pricing may vary across customers or with customer characteristics. If a customer's characteristics can capture all of his/her risks, then there is no asymmetric information, and the prices on risks across different providers should be very similar. However, if a customer's characteristics do not clearly indicate his/her risks, then the degree of disagreement in risk pricing should be large across different insurance providers due to higher information asymmetry. Therefore, to test whether price dispersion faced by customers can be partially attributed to differences in risk pricing across providers, one can examine whether customers with characteristics indicating higher levels of asymmetric information face larger price dispersion. The question then becomes which customer characteristics indicate higher levels of asymmetric information. To answer this question, notice that the existence of asymmetric information will lead to adverse selection and, in the worst-case scenario, will lead to market failure where no customers in that market segment get insured. This happens when:

$$Price_{ip} < E[Cost_{ip}|WTP_{ip} > Price_{ip}]$$

That is, at any given price, the expected costs are higher. Providers with higher costs and/or lower valuation by customers will exit such market segments and make no offers to such customers. Therefore, customer characteristics that indicate higher levels of asymmetric information should be those that predict lower offer rates from providers.

The above reasoning suggests that differences in risk pricing can be tested by examining whether customers receiving fewer quotes also face higher price dispersion. However, the issue with this proposed test is that the observed price dispersion for customers with higher levels of asymmetric information does not accurately reflect the actual price dispersion due to differences in risk pricing. This is because providers with $Price_{ip} < E[Cost_{ip}|WTP_{ip} > Price_{ip}]$ do not offer any quotes to begin with. As a consequence, the observed price dispersion is calculated from a truncated sample. As a compromise, to test whether differences in risk pricing exist, I instead test the following hypothesis:

> **Hypothesis 3** *If there are no differences in risk pricing across providers, there should be no variation in offering decisions across providers for the same customer. Individuals should either receive quotes from all providers or none at all.*

Note that to account for possible specialization in the housing market, the comparison holds fixed for the property. Moreover, the underlying assumption is that the offering decision depends solely on the relationship between price and the expected cost at that price. In this case, if we observe some customer characteristics predict an offer rate that is significantly different from 1 or 0, it suggests that there are differences in risk pricing across providers. Additionally, it implies that the differences in price dispersion due to risk pricing vary across customers since different customers have different combination of characteristics. It is worth mentioning that while differences in risk pricing can explain both facts observed in the data, they cannot overrule the explanation based on customer preferences discussed in the previous section. In other words, differences in risk pricing cannot be the only factor causing price dispersion. As shown in Section 2.5.3, NIF providers consistently charge higher prices to customers. Without higher preferences for those providers, utility-maximizing customers will not purchase the same policy at a higher price, regardless of the cause of the higher price.

Table 2.9 shows the offer rate differences for different categorical customer characteristics. To eliminate potential specialization in the property market while investigating the offer rate differences for each characteristic, I match observations by data collection date, property, and all customer characteristics other than the characteristic under investigation. For each customer, I calculate the offer rate as the number of policies they received divided by the total number of policies available in that year. The first column shows the characteristic under investigation, and the second column shows the number of matched pairs for that characteristic. The third and fourth columns show the average percentage offer rate across all pairs by the characteristic under investigation, and the last column shows the coefficient from regressing a dummy variable *offered* on the characteristic variable under investigation while controlling for matched group/pair fixed effects. The results show that there are two customer characteristics for which the offer rates significantly differ from 0 or 1. Specifically, households with someone who has declared bankruptcy or households with someone who has made claims in the past 5 years receive significantly fewer quotes. This is particularly pronounced for households with a bankruptcy history, where the offer rate decreases by nearly 40%.

Table 2.10 presents the results for non-categorical variables, with groups matched in the same manner as previously described. The offer rate only increases significantly with customer age, but with a magnitude of less than 1. However, when the two insurance policies, *Insure4Retirement* and *Saga*, which target senior customers, are excluded, there is no variation in offer rates across fictitious individuals based solely on age. Overall, the presence of customer characteristics, such as bankruptcy history and claim history, that have significant non-zero and non-unit (± 1) coefficients suggests that providers' offering decisions based on such characteristics differ. Therefore, there are differences in risk pricing across providers, and since customers have different characteristics, this also suggests that the differences in risk pricing vary across customers.

Table 2.9: Offer Rate by Customer Characteristics - Categorical Variables

Matched Group	Number of Matched Pairs	Group 1 Average Offer Rate	Group 2 Average Offer Rate	Average Offer Rate Difference (p-value)
Gender		Female	Male	
Female/Male	10	46.700	46.200	0.005 (0.78338)
Race		Non-White	White	
Non-White/White	3	56.900	57.700	-0.010 (0.80164)
Race Details		Asian	White	
Asian/White	2	47.200	48.300	-0.013 (0.77376)
		Arab	White	
Arab/White	1	76.400	76.400	0.000 (1.00000)
Marital Status		Not Married	Married	
Not Married/Married	5	63.600	64.800	-0.015 (0.60632)
Marital Details		Single	Married	
Single/Married	2	53.400	53.900	-0.006 (0.91389)
		Divorced	Married	
Divorced/Married	3	70.400	72.100	-0.019 (0.57097)
Employment Status		Not Working	Working	
Not Working/Working	23	49.100	50.300	-0.012 (0.38139)
Ownership		Mortgaged	Owned	
Mortgaged/Owned	17	50.200	50.900	-0.007 (0.63919)
Bankruptcy History		Bankrupt	Non-Bankrupt	
Bankrupt/Non-Bankrupt	20	10.900	50.200	-0.391*** (0.00000)
Claim in Past 5 Years		Claimed	Not-Claimed	
Claimed/Not-Claimed	15	42.800	46.100	-0.032* (0.05819)

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2.10: Offer Rate by Customer Characteristics - Non-Categorical Variables

Dependent Variable:	Annual Price			
Variables:	*Age*	*Number of Adults*	*Number of Children*	*Years Without Claims*
Estimate	0.0006***	-1.92×10^{-17}	-0.0095	-0.0009
(Std. Error)	(0.0001)	(2.81×10^{-17})	(0.0071)	(0.0006)
Fixed-effects				
Matched Group	Yes	Yes	Yes	Yes
Fit statistics				
Observations	4,094	445	2,225	4,183
R^2	0.08808	0.11842	0.09108	0.11433

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

2.6.2 Differences in Markups Charged

As Equation (2.4) suggests, the observed price dispersion faced by a customer and the heterogeneity in price dispersion across customers can both be explained by different markups charged by various insurance providers. This explanation aligns with the customer preference theory discussed in Section 2.5. However, the empirical evidence in Section 2.5.3 fails to account for the significant differences in price dispersion across customers. The existence of differences in risk pricing addresses this gap. Nonetheless, this does not imply that the relative differences in markups charged by different providers do not vary across customers. It only indicates that these differences do not seem to vary significantly with self-disclosed customer characteristics and, therefore, are unlikely to be based on customer preferences. It remains possible that markups and their relative differences vary across customers in other ways.

One potential alternative explanation is provided by search cost theories (e.g., Stigler, 1961; Reinganum, 1979; Carlson and McAfee, 1983; Baye et al., 2006). If customers face different search costs, they will encounter varying levels of price dispersion[14]. However, without knowing the search costs faced by these fictitious individuals, I cannot test any predictions derived from such theories. More importantly, search cost-based theories do not seem well-suited here, given that the market studied is an online comparison website. Even if the prices listed on the website are influenced by sales channels other than the comparison website, search frictions are still unlikely to be the main cause of the observed price dispersion for several reasons. First, as already mentioned in Section 2.2, buying insurance online is quite common in the UK. More than 50% of people purchase home insurance online, and many use PCWs to compare prices before making purchase decisions, making search costs less relevant. Second, the FCA report found that insurance providers set different markups across different distribution channels, suggesting prices on PCWs are less likely to be affected by search costs

[14] Although search cost theories do not usually distinguish costs and markups, they suggest that markups can vary with search costs.

faced by customers purchasing through other distribution channels. Furthermore, customers shopping through PCWs are likely to be different from those shopping through other channels, and thus even if there are search costs faced by customers shopping from other channels, they are less likely to explain the price dispersion patterns observed on the PCW. If search cost-based theories cannot provide a convincing explanation, then could there be another explanation, besides differences in risk pricing, for the price dispersion observed on the PCW? Further investigation shows that some providers seem to randomize their prices.

To understand how different insurance providers vary their prices across different individuals, I investigate how their prices change with different customer characteristics, all of which are binary-type. To do so, I first match quotes by data collection date, property, policy, policy choices, and all individual characteristics except for the one under investigation. Each matched pair therefore only differs in one individual characteristic[15]. Each provider will have multiple such matched pairs for every characteristic under investigation. I then calculate the price difference for each matched pair and group providers based on the price differences of all their matched pairs.

The results for the policyholder characteristics are shown in Figure 2.3. Among the 56 insurance providers with matched pairs that only differ in gender, the majority—38 providers (29 IF and 9 NIF)—do not price discriminate based on gender across all their matched pairs, and only one provider consistently charges more for females across all its matched pairs. Notably, 17 providers adopt mixed pricing strategies, meaning the price difference across all their matched pairs is not consistently positive, negative, or zero. Thus, all else being equal, being female could result in higher, lower, or the same prices as being male. Similarly, for race, the majority of 42 providers (out of 45) do not vary their prices with customer race, but one provider consistently charges higher prices for individuals with non-white-sounding names. Regarding marital status, while most providers either adopt mixed pricing strategies or do not discriminate based on marital

[15]For gender, matched individuals also have different first names to match with gender.

status, two providers consistently charge more for individuals who are not married. For working status, although most insurance providers (46 out of 52) adopt a relatively random pricing strategy, one provider consistently charges more for individuals who are not working, three providers charge more for those who are currently working, and two do not price discriminate based on working status.

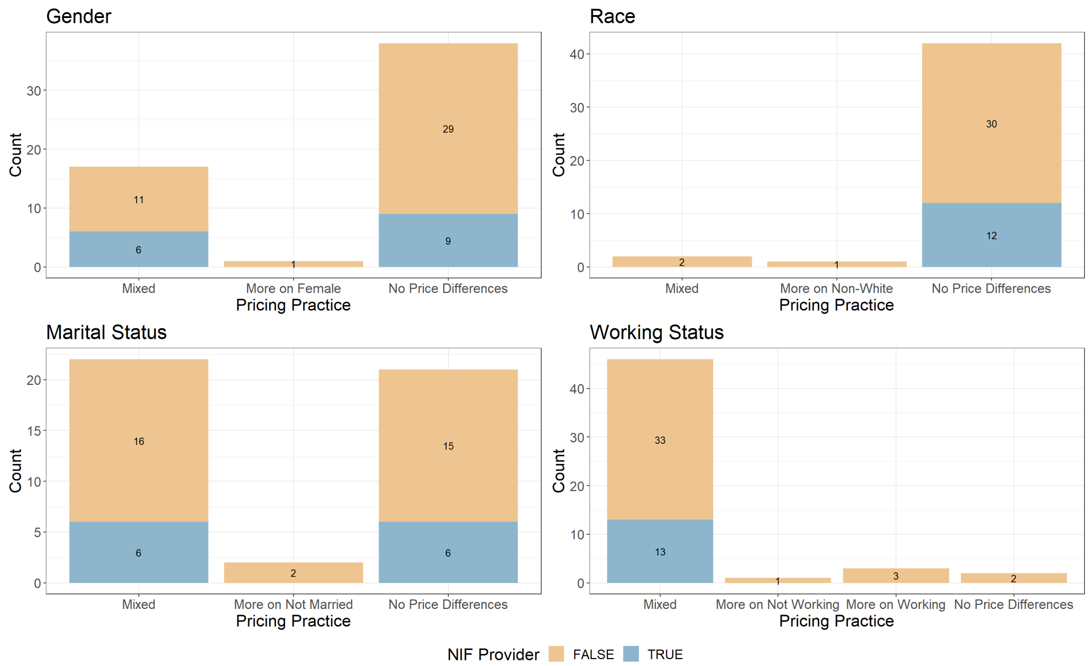


Figure 2.3: Pricing Practices by Policyholder Characteristics

Note: The figure summarizes the pricing practices of different providers. The x-axis shows groups of providers based on the price differences from all eligible pairs of quotes, with each pair matched by all characteristics except the one under investigation. Providers with all price differences of 0 fall under "No Price Differences." Providers with a mix of positive, negative, and zero price differences fall under "Mixed." Otherwise, providers fall into groups corresponding to the sign of the price differences of all their matched pairs.

Overall, the results in Figure 2.3 suggest that some insurance providers are randomizing their prices, as evidenced by the existence of providers adopting mixed pricing strategies on certain policyholder characteristics. Such randomization is more likely to be on markups rather than on risks, as risk pricing should remain stable over short periods. Furthermore, the results indicate that a few providers consistently price discriminate based on protected characteristics such as gender, race, and marital status[16]. Consistent with the results in Section 2.5.3,

[16] According to the UK Equality Act 2010, age, disability, gender reassignment, marriage and

NIF providers did not consistently price discriminate based on policyholders' self-disclosed personal characteristics.

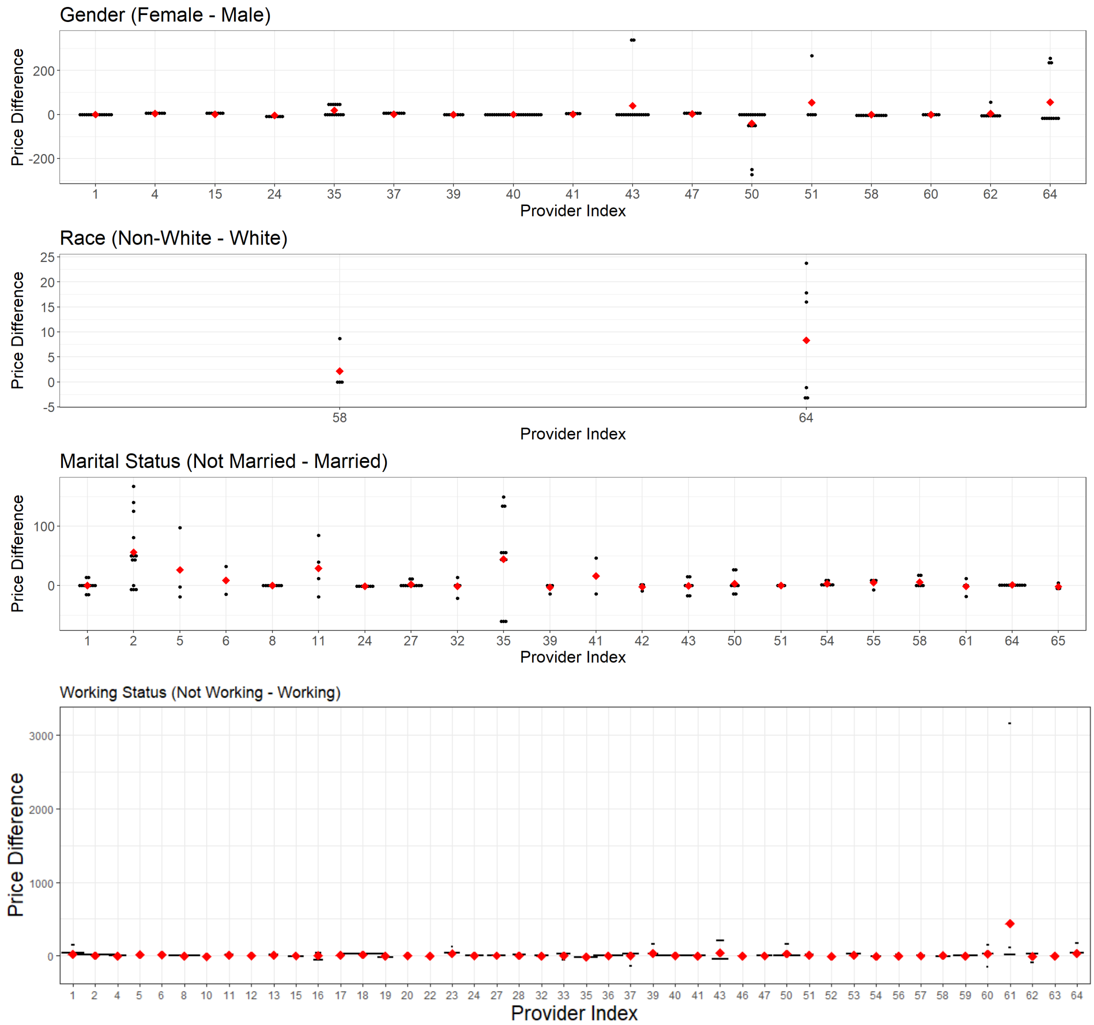


Figure 2.4: Pricing Difference by Policyholder Characteristics

Note: The figure shows the distribution of price differences for providers following mixed-pricing strategies. The y-axis represents the price differences, and the x-axis represents the provider identifiers. The black dots/lines centered around each provider indicate the quote pairs with specific levels of price differences. The red diamond-shaped dot represents the average price difference across all eligible pairs from a provider.

To further investigate how providers adopting mixed pricing strategies price different policyholder characteristics, Figure 2.4 displays the distribution of price differences for all matched pairs for each provider using mixed pricing strategies. The x-axis represents the identifier for each provider, and the y-axis represents

civil partnership, pregnancy and maternity, race, religion or belief, sex, and sexual orientation are protected characteristics and should not be used for insurance pricing except for age and disability.

the price difference in British pounds, calculated as indicated by the title of each subfigure. Each small black dot represents the price difference of a matched pair, while the average price difference across all pairs is represented by the red diamond-shaped dot. The subfigure for gender shows that among those adopting mixed pricing strategies, most providers do not significantly adjust their prices based on gender, resulting in price differences that are not far from zero. As for race, only two providers randomize their prices on this dimension, both charging, on average, higher prices to individuals with non-white-sounding names. However, a larger sample is needed for statistical inference. Compared to the above two protected characteristics, providers adopting mixed strategies vary their prices more based on the marital status of an individual. Lastly, most providers using mixed pricing strategies do not vary their prices significantly with working status.

A similar investigation was conducted on three categorical household characteristics, which are arguably more likely to be used in risk pricing. Figure 2.5 shows that, compared to the pricing on policyholder characteristics, the majority of insurance providers either consistently price discriminate based on household characteristics or adopt mixed pricing strategies for household characteristics. If these household characteristics are indeed used in risk pricing, it is not surprising that some providers consistently incorporate such characteristics into their pricing. The fact that not all providers have consistent price differences in the same direction supports the alternative explanation of differences in risk pricing. More interestingly, however, a significant number of providers adopt mixed pricing strategies for these characteristics. As argued earlier, the portion of the price based on risk should be relatively stable over a short time frame; thus, the randomness in prices from those providers must come from the randomization of markups.

Figure 2.5: Pricing Practice by Household Characteristics

Figure 2.6 plots the distribution of price differences for providers adopting mixed pricing strategies on the three household characteristics. While no statistical inference is conducted, a glance at the three figures reveals that the average price differences for most providers are either zero or positive. This suggests that despite the randomness in prices, most providers tend to price these household characteristics in a certain direction. More specifically, most providers adopting mixed pricing strategies tend to charge more on households with a mortgage, a history of bankruptcy, or claims made in the past five years. These directions of price differences are consistent with those of the providers who consistently price in such characteristics in Figure 2.5. Therefore, it is quite likely that the price differences from those mixed-pricing providers capture both differences in risks and the randomness in markups.

Overall, the investigation of providers' pricing practices offers another explanation for the observed price dispersion in the data: some insurance providers appear to randomize the markups they charge customers. One caveat, however, is that the observed randomness might capture modeling errors. If the characteristic under investigation interacts with other customer characteristics, then the observed inconsistency in price differences might result from these interaction terms. For instance, suppose a provider prices marital status together with the number of children. A married customer with no children may receive a higher price than a similarly situated but unmarried customer, while a married customer with four children might receive a lower price than a similarly situated but unmarried customer. If this is the case, then the evidence presented above as support for markup randomization actually suggests that different providers have different risk-pricing models, thus supporting the first alternative explanation. Unfortunately, without knowing the exact pricing model of each insurance provider, it is difficult to distinguish between these two possibilities.

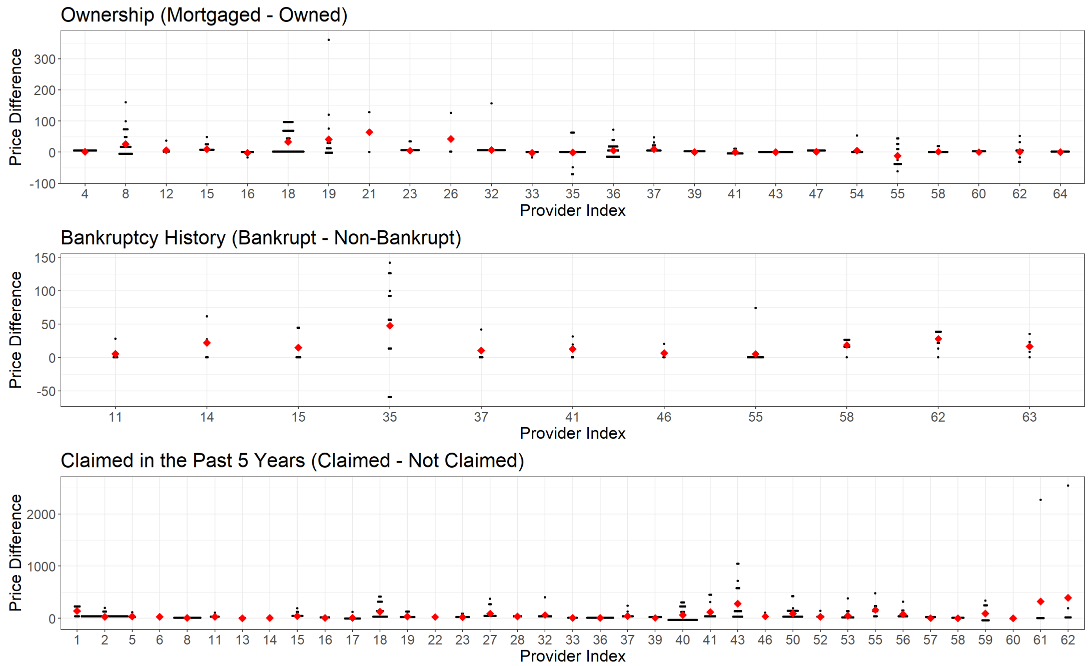


Figure 2.6: Pricing Practice by Household Characteristics

2.7 Conclusion

This paper investigates the price dispersion of building insurance policies in the UK home insurance market. Using real properties and fictitious individuals as inputs, I obtained quoted annual prices from one of the leading PCWs in the UK and identified two key facts: First, there is significant price dispersion faced by individual customers. Second, the degree of price dispersion varies considerably across different customers.

The primary explanation for these observations is that some customers may value additional features offered by certain insurance providers, leading to higher prices for seemingly identical policies. This indicates a form of unobserved product differentiation where customers' preferences for non-policy features influence their willingness to pay. However, the empirical results suggest that the preference-based explanation is not the entire story. Additionally, two alternative explanations account for the observed price dispersion patterns: differences in risk pricing and the randomization of markups. Differences in risk pricing suggest that providers assess the risks of insuring customers differently, leading to variations in quoted prices. Evidence also suggests that some providers may randomize the markups they charge, adding another layer of price variation.

This paper has certain limitations. With the current data, it is not possible to entirely rule out the impact of search frictions on price dispersion. Therefore, the findings should be viewed as complementary to existing search-cost based theories on price dispersion. Moreover, the study cannot disentangle and quantify the contributions of differences in risk pricing versus markups to the overall price dispersion. For a more comprehensive understanding and welfare analysis, additional data on actual transactions and claims is needed.

In summary, while the findings highlight the importance of customer preferences and reveal the complexities of risk assessment and pricing strategies in the insurance market, further research with more granular data is essential to fully understand the dynamics of price dispersion in this sector.

Chapter 3

Can Green Bonds Make the World Greener?

Abstract

Can corporate green bonds make the world greener? To answer this question, I analyze the corporate green bond market through a theoretical and empirical approach. Using a simple theoretical framework, I demonstrate that green bonds can positively impact the economy under certain conditions, particularly when financially constrained firms use green bonds as a commitment device to invest in greener but less profitable projects. To empirically test this condition, I measure the financial constraint of both green bond issuers and non-issuers with available ESG data. The results reveal that green bond issuers are typically greener and less financially constrained compared to non-issuers, suggesting that they are less likely to need green bonds as a commitment device. Consequently, under current market conditions, the existence of green bonds does not appear to significantly influence firms' environmental behavior.

3.1 Introduction

The corporate green bond market has been growing rapidly ever since a Swedish property company, Vasakronan, issued the first corporate green bond in 2013[1]. The aggregate annual issuance amount has increased from approximately \$3.97 billion in 2013 to over \$162 billion in 2020, according to calculations based on Bloomberg's green bonds datab3.Ase. This corresponds to an average annual growth rate of around 70%[2]. Despite the existence of several frameworks for green bond issuance, none are legally binding[3]. Nonetheless, it has become a common market practice for green bond issuers to have their bonds verified by external reviewers and to provide regular reports on their green projects and the use of proceeds. Most external reviewers follow the framework established by the Green Bond Principles[4]. These reviewers ensure that the proceeds raised from the green bonds are used exclusively for the underlying green projects and provide their own evaluation reports on the issuers' green bonds. The average base fee for third-party review services is around \$25,000[5].

Given the extra effort and costs associated with issuing green bonds, it is natural to question whether green bonds effectively contribute to making the economy greener. This is a challenging question, as it requires comparing current market outcomes with green bonds to a counterfactual world without them. Alternatively, it could be answered by randomizing the availability of green bonds across different firms (e.g., through exogenous policies). However, given the endogenous development of the green bond market and the absence of such exogenous policies, answering this question empirically is very difficult. Even if we observe that firms become greener after issuing green bonds (e.g., by reducing their GHG

[1]Information from: https://www.climatebonds.net/market/explaining-green-bonds

[2]Bloomberg has comprehensive coverage of green bonds. However, the exact numbers might still vary slightly.

[3]The European Union is currently developing a green bond standard to unify different frameworks, but it remains a voluntary standard.

[4]This is a voluntary process guideline established by the International Capital Market Association in 2014. The most recent edition was published in June 2021.

[5]This figure is the average of quotes obtained from several companies that provide external review services. The exact fees depend on various parameters, such as the timeline of the issuance and the number of use of proceeds categories.

emissions), we cannot conclusively attribute this to the green bonds, as these issuers might have reduced their emissions even without issuing green bonds. Consequently, most research on green bonds has focused on identifying pricing premiums or studying the reactions of issuers' stock prices following the issuance of green bonds (e.g. Zerbib, 2019; Larcker and Watts, 2020; Tang and Zhang, 2020; Flammer, 2021). The results on pricing premiums are mixed, with most recent studies finding no significant pricing premium for green bonds, indicating that investors are not generally willing to pay extra or accept lower returns for green bonds.

However, this paper demonstrates through a simple model that the existence of a pricing premium—defined as the difference between the yield of a non-green bond and that of an otherwise comparable green bond—is neither a necessary nor a sufficient condition for green bonds to have a positive impact on the environment. The crucial condition for green bonds to make a positive environmental impact is that they are used by financially constrained firms as a commitment device to credibly invest in greener projects that would otherwise not be undertaken, assuming these projects are financially less attractive than less green alternatives. When there is abundant green capital in the market, there will not be any pricing premium since the break-even condition for green investors remains the same with or without green bonds. Conversely, when green capital is scarce, the pricing premium arises only because issuing green bonds entails additional costs. However, depending on the assumptions regarding the utility function of green investors and the specific values of the model parameters, green bonds may not make any difference even if a pricing premium exists.

To empirically test the implications of the theoretical model, I combine corporate green bonds data from Bloomberg with Compustat firm financial data and Eikon ESG data to investigate whether there are financially constrained issuers in the current corporate green bond market. Using the SA index developed by Hadlock and Pierce (2010) as a measure of firms' financial constraints, I find that green bond issuers are generally less financially constrained and have higher environmental scores compared to firms that have never issued green bonds. This result suggests that green bonds are mostly issued by firms that are already relatively clean and not significantly financially constrained, and thus are less likely to be used as a commitment device to undertake greener but less profitable projects. Further investigation reveals that green bond issuers tend to issue green bonds when they have abundant cash, ruling out the possibility that firms issue green bonds during periods of greater financial constraint. Consequently, in the current corporate green bond market, green bonds do not seem to have a significant environmental impact, as firms' behaviors are unlikely to be affected by the existence of green bonds. I further estimate the pricing premium for a subset of green bonds matched with non-green bonds from the same issuer. Consistent with the findings of Flammer (2021), there is no significant pricing premium on average. Using an even smaller matched sample with ESG data, I also find no significant relationship between pricing premium and firms' level of greenness. These results suggest that the utility investors derive from green bonds might be independent of firms' level of greenness, and that the green capital is currently likely scarce. If this is the case, green bonds could have a more significant impact in the future when there are enough investors who derive non-pecuniary utility from green bonds. However, given the small matched sample, this conclusion remains tentative.

This paper has several limitations. First, the model is static and only explores one potential channel through which green bonds could positively impact the environment. Second, the measures of firms' financial constraints are imperfect. Ideally, it would be beneficial to have data on the investment opportunities or potential projects of these firms, but such data is difficult to obtain. Alternatively, future studies could leverage quasi-experiments to better capture the financial constraints and investment behaviors of firms issuing green bonds. The remainder of the paper is organized as follows: Section 3.2 presents the theoretical framework, and Section 3.3 describes the data and the empirical results from testing the implications of the theoretical framework. Section 3.4 concludes.

3.2 Theoretical Framework

In this section, I use a parsimonious model to show under what circumstances green bonds can help improve the greenness (or lower GHG emissions) of the economy. There is an emerging literature on modeling the conditions under which ESG or impact investing could positively impact society (e.g., Chowdhry et al., 2019; Landier and Lovo, 2020; Opp and Oehmke, 2020; Pástor et al., 2020). However, as far as I know, no such model is tailored specifically to the corporate green bond market. Here, I use a simple framework to study under what conditions the existence of green bonds can make a positive difference to the environment. I first evaluate the model assuming both green investors and non-green investors face a competitive capital market, and then consider the case where green investors have less aggregate capital than the aggregate demand from firms.

3.2.1 Model Setup

Consider an economy populated with a continuum of firms, with the total mass normalized to 2. Firms can be ranked by their greenness, λ, where $\lambda \in [-1, 1]$, with the dirtiest firms at -1 and the cleanest at 1. The λ represents the historical social externality generated by each firm, such as the negative of the total GHG emissions. For simplicity, I will refer to firms with $\lambda > 0$ as green firms (GF) and firms with $\lambda \leq 0$ as non-green firms (NGF).

Each firm is run by a risk-neutral entrepreneur and can invest in a green project requiring an initial investment of I today ($t = 0$). In the next period ($t = 1$), the green project generates a pecuniary payoff X_G with probability θ, and with probability $1 - \theta$, the green project generates 0. Both X_G and θ are constant across all firms. Green projects differ in their level of greenness $g_G(\lambda)$. Assume that $g_G(\lambda) > 0$ for $\lambda \in [-1, 1]$, $g'_G(\lambda) > 0$, and $g''_G(\lambda) \leq 0$. This ensures that green projects of all firms generate positive externalities and that greener firms have greener projects. Besides the green project, non-green firms ($\lambda \leq 0$) can choose a non-green project with the same initial investment I today, and it generates a pecuniary payoff X_{NG} with probability θ and 0 with probability $1-\theta$. The non-green project also generates an externality $g_{NG}(\lambda)$. Assume that $g_{NG}(\lambda) \leq 0$ for $\lambda \in [-1, 0]$, $g'_{NG}(\lambda) > 0$, and $g''_{NG}(\lambda) \geq 0$. This means the dirtier firms' non-green projects are also dirtier. The externality from both green and non-green projects is assumed to be independent of the project's financial outcomes. Additionally, for a meaningful trade-off, assume $I < \theta X_G < \theta X_{NG}$, so that both green and non-green projects have positive NPV and that green projects have lower NPV than non-green projects. Without loss of generality, also assume that the discount rate $r = 0$ in this economy.

The entrepreneur of each firm is endowed with A amount of capital. For both green firms and non-green firms, a proportion $\rho \in (0, 1)$ of firms' entrepreneurs have $A < I$ and $1-\rho$ of firms' entrepreneurs have $A \geq I$. Each firm can choose to finance an amount F by issuing a security that promises a repayment of k per unit financed (k is essentially the gross return). Assume that the maximum amount a firm can finance is I (i.e. $F \leq I$). This assumption implies that, although non-green firms would like to implement both green and non-green projects, given both are positive NPV projects, only non-green firms with $A \geq I$ can achieve this. Non-green firms with $A < I$ cannot implement both due to financial constraints. Based on the above assumptions, entrepreneurs' expected utilities can be written as:

$$\text{For GF with } \lambda > 0: \quad U_{GF}(F) = \theta\,[X_G - kF] + A - (I - F)$$

$$\text{For NGF with } \lambda \leq 0:$$

$$A < I: \quad U_{NGF,\,A<I}(F \mid i) = \theta\,[X_i - kF] + A - (I - F), \; i \in \{G, NG\}$$

$$A \geq I: \quad U_{NGF,\,A\geq I}(F) = \theta X_G + \theta X_{NG} - I - \theta k F + A - (I - F)$$

Firms can finance through a continuum of risk-neutral investors, each of whom has I for investing. Investors can be categorized into two types $t \in \{GI, NGI\}$. *NGIs* are non-green investors who only care about the financial returns, whereas

GIs are green investors who not only care about financial returns but also the overall greenness of the firms they invest in, regardless of the project's financial outcomes. Specifically, *GIs* consider both the historical externality of a firm and the externality from the firm's future projects (i.e., $\lambda + \sum_{i \in \{G,NG\}} g_i(\lambda)$). Assume that the total greenness of a firm enters into the utility of a green investor linearly and is proportional to the amount that the green investor invests in the firm. The expected utility functions of the two types of investors can be written as:

$$U_{NGI} = \theta k F - F$$

$$U_{GI} = \theta k F - F + \alpha F \left[g_i(\lambda) + \lambda \right], \text{ if invest in GF or in NGF with } A < I$$

$$U_{GI} = \theta k F - F + \alpha F \left[g_G(\lambda) + g_{NG}(\lambda) + \lambda \right], \text{ if invest in NGF with } A \geq I$$

where $\alpha \in (0,1)$ is a parameter that determines the extent to which green investors internalize the overall externality generated by a firm they invest in. Throughout the paper, I assume that non-green investors have more than enough capital to finance all firms and that they face a competitive capital market, so that in equilibrium all non-green investors break even ($U_{NGI} = 0$). This assumption implies that the gross return k that a firm needs to promise to non-green investors to secure financing is $\frac{1}{\theta}$ and also implies that a firm's outside option is the utility it can get from financing through non-green investors. The assumption regarding the availability of green capital will be specified in each model.

It is worthwhile to clarify the timeline here before jumping into the models. There are two periods in the models: $t = 0$ and $t = 1$. At $t = 0$, firms choose the amount F that they would like to finance and issue securities to finance F. Investors invest, and k for each firm is determined in equilibrium. Once a firm secures its financing with a promised k to investors, the firm then makes its investment decisions. At $t = 1$, the firm repays investors the promised kF if the project(s) succeed; otherwise, the firm pays nothing.

3.2.2 Baseline Model

In the baseline model, I assume that the mass of green investors is larger than the mass of all firms. Therefore, there is sufficient green capital, and green investors also face a competitive capital market. The participation constraint (PC) for green investors ($U_{GI} \geq 0$) holds with equality, and green investors break even. Since green investors incorporate a firm's overall greenness in their utilities and firms have different levels of greenness, the break-even condition for green investors determines the k a firm with a specific λ needs to promise. Mathematically, green firms choose F through:

$$\max_{0 \leq F \leq I} U_{GF} = \theta X_G - \theta k F + A - (I - F)$$

$$s.t. \quad U_{GI} = \theta k F - F + \alpha F \left[g_G(\lambda) + \lambda \right] = 0$$

The break-even condition for green investors implies that

$$k = \frac{1 - \alpha[g_G(\lambda) + \lambda]}{\theta} \equiv k_{GF} \tag{3.1}$$

Substituting k with k_{GF}, the firm's optimization problem then becomes:

$$\max U_{GF} = \theta X_G - I + \alpha F \left[g_G(\lambda) + \lambda \right] + A \quad s.t \quad 0 \leq F \leq I$$

Since $g_G(\lambda) + \lambda > 0$ when $\lambda > 0$, all green firms would like to exhaust their financing capacity by choosing $F = I$ to maximize their utilities, regardless of the level of A their entrepreneurs are endowed with. At the level of k_{GF} in (3.1), the PC of non-green investors will not be satisfied, and thus green firms will only finance through green investors. In equilibrium, the expected utility of green firms will be

$$U^*_{GF} = \theta X_G - I + \alpha I[g_G(\lambda) + \lambda] + A \tag{3.2}$$

So, in addition to the original capital A, a green firm will also gain the NPV of the green project plus all of the extra utility green investors derive from investing in the green firm. From equations (3.1) and (3.2), one can see that the gross return k_{GF} required for each green firm decreases with λ, while the expected utility of the firm increases with λ. Therefore, with sufficient green capital, the greener a firm is, the lower the financing cost it needs to pay.

Similarly, one can derive the required gross returns from green investors for non-green firms with $A \geq I$ and $A < I$, respectively:

$$k = \frac{1 - \alpha[g_G(\lambda) + g_{NG}(\lambda) + \lambda]}{\theta} \equiv k_{NGF,\, A \geq I} \tag{3.3}$$

$$k = \begin{cases} \frac{1-\alpha[g_G(\lambda)+\lambda]}{\theta} \equiv k_{NGF,\, A<I}(G), & \text{if green project is chosen} \\ \frac{1-\alpha[g_{NG}(\lambda)+\lambda]}{\theta} \equiv k_{NGF,\, A<I}(NG), & \text{if non-green project is chosen} \end{cases} \tag{3.4}$$

Since firms can always finance through non-green investors with $k = \frac{1}{\theta}$, they will only choose green-investor financing if the utility from it is larger than the utility from non-green investor financing. Furthermore, for a firm with positive overall greenness (i.e., firms with $\lambda + \sum_{i \in G,NG} g_i(\lambda) > 0$), it is always optimal to set $F = I$, given that the firm chooses green-investor financing. Therefore, for firms with $A \geq I$:

$$U^*_{NGF,\, A \geq I} = \theta X_G + \theta X_{NG} - 2I + A + max\{0, \alpha I[g_G(\lambda) + g_{NG}(\lambda) + \lambda]\} \tag{3.5}$$

For non-green firms with $A < I$, however, they can only get financed through non-green investors and receive:

$$U^*_{NGF,\, A<I} = \theta X_{NG} - I + A \tag{3.6}$$

This is because capital-constrained non-green firms face a commitment issue. Since firms invest after they secure financing, non-green firms have an incentive to choose non-green projects over green projects, as non-green projects have higher NPV than green projects (i.e., $\theta X_{NG} - I > \theta X_G - I$). In a competitive capital market, where firms receive the project NPV, capital-constrained non-green firms will always choose the non-green project once they secure financing. Anticipating this, green investors will require $k_{NGF,A<I}(NG)$ in (3.4), which is larger than $\frac{1}{\theta}$, the cost of financing through non-green investors. Therefore, in equilibrium, capital-constrained non-green firms can only secure financing from non-green investors.

3.2.3 A Commitment Device

Suppose now firms can pay a fixed cost c to a credible third party who can monitor the firms' investments, ensuring that they invest in the project they financed. This resembles the option of issuing green bonds with external reviews in practice. This additional choice is essentially a commitment device. Therefore, firms that face a commitment issue in the baseline model in Section 3.2.2 (i.e., those non-green firms with $A < I$) could increase their utility by paying for the commitment device, given the following condition (IC) holds:

$$\theta X_G - \theta k I + A - c \geq \theta X_{NG} - I + A, \quad \text{that is}$$

$$k \leq \frac{1}{\theta} - \frac{X_{NG} - X_G}{I} - \frac{c}{\theta I} \quad \text{or} \quad g_G(\lambda) + \lambda \geq \frac{\theta(X_{NG} - X_G) + c}{\alpha I} \tag{3.7}$$

The last part of Equation (3.7) is derived by plugging in the required $k_{NGF,A<I}(G)$ in (3.4). It implies that a financially constrained non-green firm will only pay for the commitment device (or issue a green bond with external reviews) if its overall greenness after considering the green project it is financing exceeds a positive threshold (the right-hand side in Equation (3.7)). A more intuitive way to look at Equation (3.7) is to rewrite it as $\alpha I[g_G(\lambda)+\lambda] \geq \theta(X_{NG}-X_G)+c$, which suggests that a firm will only pay for the commitment device if the benefit it gets from green investors exceeds the cost. The first component of the cost, $\theta(X_{NG} - X_G)$, measures the financial payoff the firm forgoes by choosing a green project over a more profitable non-green project, and the second component is the cost of the commitment device. Suppose the parameters in this model are consistent with the

existence of such financially constrained non-green firms. Then in equilibrium, non-green firms with $A < I$ and with λ satisfying the above condition will buy the commitment device and get:

$$U^*_{NGF,A<I} = \theta X_G - I + \alpha I[g_G(\lambda) + \lambda] + A - c \tag{3.8}$$

through green-investor financing with $k = k_{NGF,A<I}(G)$ in Equation (3.4). Moreover, the existence of such a commitment device also improves the overall greenness of the economy (or reduces the amount of GHG emissions) by:

$$\int_{\lambda \in \mathbf{\Lambda}} [g_G(\lambda) - g_{NG}(\lambda)]\, d\lambda \tag{3.9}$$

where $\mathbf{\Lambda}$ is the set of $\lambda \leq 0$ that satisfies Equation (3.7) for non-green firms with $A < I$. Therefore, under these assumptions, only non-green firms with capital constraints will issue green bonds (i.e., firms with $\lambda \leq 0$ and $A < I$). Green firms can always secure financing from green investors, and non-green firms with $A \geq I$ will always invest in both green and non-green projects, regardless of whether they finance from green investors or not. However, the results could be generalized to firms with any λ as long as these firms face mutually exclusive projects, and the greener project is less profitable than the less green one.

3.2.4 Additional Utility

What if green bonds can not only be used as a commitment device but also give green investors additional utility on top of what they already get from investing in firms with an overall positive level of greenness? Assume that green investors receive additional utility b per unit of investment in green bonds. This additional utility can be viewed as extrinsic rewards, while the original $\alpha F[\lambda + \sum_{i \in G,NG} g_i(\lambda)]$ can be interpreted as utility derived from intrinsic motivation. This assumption can be justified by the fact that many ESG scores for the financial sector account for such investments. For instance, a few variables used in Thomson Reuters' ESG score calculation explicitly state that responsible environmental investing, such as green bonds, is relevant for the financial sector. Although there is no consensus on how a higher ESG score benefits a firm, there is evidence showing that the sudden categorization of funds as high-sustainability funds increases demand for such funds (e.g., Hartzmark and Sussman, 2019; Ceccarelli et al., 2024). With the additional b per unit of investment, the green investors' utility from investing in green bonds issued by different firms is:

$$U_{GI} = \theta k F - F + \alpha F \, [\, \lambda \, + \sum_{i \in \{G,NG\}} g_i(\lambda) \,] + bF$$

Since once a firm chooses to finance from green investors, it will always exhaust its financing capacity, the green investors' utility function can be simply written as:

$$U_{GI} = \theta k I - I + \alpha I \, [\, \lambda \, + \sum_{i \in \{G,NG\}} g_i(\lambda) \,] + bI \tag{3.10}$$

Given that the supply of green capital is larger than the demand, the required gross returns in the competitive market equilibrium for green bonds become:

$$k^{GB} = \frac{1 - \alpha \, [\, \lambda \, + \sum_{i \in \{G,NG\}} g_i(\lambda) \,] - b}{\theta} \tag{3.11}$$

Similar to the derivation of Equation (3.7), one can show that the ICs of different firms imply that the maximum gross returns different firms can accept from green investors are:

$$\text{For NGFs with } \; A < I: \quad k \leq \frac{1}{\theta} - \frac{X_{NG} - X_G}{I} - \frac{c}{\theta I} \tag{3.12}$$

$$\text{For GFs and NGFs with } \; A \geq I: \quad k \leq \frac{1}{\theta} - \frac{c}{\theta I} \tag{3.13}$$

All of them decrease by $\frac{c}{\theta I}$ compared to their corresponding acceptable maximum gross returns in a market without green bonds. By substituting (3.11) into (3.12) and (3.13), one can easily rewrite the ICs as constraints on λ. It is easy to show that as long as $bI - c \geq 0$, all firms' ICs are relaxed by $\frac{bI-c}{\alpha I}$. Specifically, for those financially constrained non-green firms, the IC for them becomes:

$$\theta X_G - I + \alpha I[g_G(\lambda) + \lambda] + A + bI - c \geq \theta X_{NG} - I + A,$$

$$\text{or} \quad g_G(\lambda) + \lambda \geq \frac{\theta(X_{NG} - X_G)}{\alpha I} - \frac{bI - c}{\alpha I} \tag{3.14}$$

Therefore, keeping the same assumptions as in Section 3.2.3, the existence of green bonds enhances the overall greenness of the economy even further, as the set $\mathbf{\Lambda}$ in Equation (3.9) is larger when the IC of financially constrained non-green firms is relaxed. Furthermore, green firms and non-green firms with $A \geq I$ that could originally secure financing from green investors without issuing green bonds will now also issue green bonds to obtain the additional utility of $bI - c$. However, the green bonds will not change the greenness level of these firms.

3.2.5 Insufficient Green Capital

In the previous models, when there is more green capital than the aggregate financing capacity of all firms, the existence of green bonds could increase the greenness of the economy by allowing the green projects of some financially constrained non-green firms that otherwise would not be financed to be credibly financed by green investors. In this section, I deviate from the competitive market assumption for green investors and assume that the aggregate supply of green capital, I_G, is less than the aggregate demand from firms that would like to issue green bonds.

Additional Utility Extension

Keep all other assumptions the same as in Section 3.2.4, except that now firms need to compete for the scarce green capital. Since green investors obtain additional utility from green bonds, firms financing from green investors will always prefer to issue green bonds. Additionally, since, by the assumptions in Section

3.2.1, both $g_G(\lambda)$ and $g_{NG}(\lambda)$ are increasing functions of λ, the utility function of green investors also increases with λ. This suggests that, for the same k, green investors always prefer firms with larger λ. As a result, firms with larger λ can lower their k to the point that the utility green investors get from investing in them is the same as the utility green investors get from investing in the marginal firm.

Consider the case when $I_G < I$. In this scenario, only the greenest of the green firms (i.e., those with $\lambda > 0$) will issue green bonds and get financed by green investors in equilibrium. To see this, let λ_M denote the greenness level of the marginal firm. Green firms will increase k_{GF} in Equation (3.11) to compete for the scarce green capital until financing from green investors is no better than financing from non-green investors, that is, until the utility they get financing from green investors equal to that when finance from non-green investors. Since firms with higher λ provide green investors with higher additional utility, they do not need to increase their promised returns as much as firms with relatively lower λ. The competition continues until the marginal firm faces $k^{GB} = \frac{1}{\theta} - \frac{c}{\theta I} \equiv k_M^{GB}$ and is indifferent between financing through either type of investor. All firms with $\lambda > \lambda_M$ can get financed by green investors at returns lower than $k_M^{GB} = \frac{1}{\theta} - \frac{c}{\theta I}$. Combining this with Equation (3.10), we can calculate the utility green investors get from investing in the marginal firm:

$$U_{GI}^{*} = \alpha I[g_G(\lambda_M) + \lambda_M] + bI - c \equiv M \tag{3.15}$$

Given this level of utility, all firms with $\lambda > \lambda_M$ will set k^{GB} such that $U_{GI}(k^{GB}) = M$, thereby maximizing their utility while still attracting green investors. That is:

$$k^{GB} = \frac{1 - \alpha[g_G(\lambda) + \lambda] - b}{\theta} + \frac{M}{\theta I} \tag{3.16}$$

The utility these green-bond issuers get in equilibrium is then given by:

$$U_{GF}^{*GB} = \theta X_G - I + \alpha I[g_G(\lambda) + \lambda] + A + bI - c - M \tag{3.17}$$

Under the assumption of scarce green capital ($I_G < I$), it can be shown that the marginal firm remains the same, with or without green bonds. Therefore, the existence of green bonds does not impact the environment, nor does it increase the utility of green-bond issuers[6]. It only benefits green investors by increasing their utility by $bI - c$. This is mainly due to the assumption that green investors obtain higher utility from greener firms. When green capital is scarce, instead of channeling capital to incentivize capital-constrained non-green firms to undertake green projects, green investors prioritize investing in green firms that will implement green projects even in the absence of green capital. However, for $I_G > I$ but still smaller than the aggregate demand for green capital, the existence of green bonds could help improve the greenness of the economy by allowing financially constrained firms to commit to green project investments, provided these firms are not excessively polluting (i.e., λ not too negative). Otherwise, other financially unconstrained non-green firms may outcompete them and secure the scarce green capital.

Utility Substitution

One concern about green bonds from critics (e.g. Wighton, 2019) is that exaggerating the benefits of green bonds might make investors complacent, choosing to invest in green bonds rather than engaging in more effective environmental actions. To analyze this statement, I assume that financially constrained non-green firms have $\lambda \in [-\rho, 0]$, making them the relatively greener type among the non-green firms. Furthermore, while still assuming insufficient green capital, I adjust the assumption in Section 3.2.4 regarding the utility green bonds provide to green investors. Suppose, instead of giving green investors additional utility b per unit of investment on top of what they derive from firms' overall greenness, issuing green bonds causes investors to ignore the greenness level of a firm, so that green investors only receive b per unit of investment from holding green bonds.

[6] One can plug (3.15) into (3.17), and see that $U_{GF}^{*GB} = \theta X_G - I + \alpha I[g_G(\lambda) + \lambda] + A - \alpha I[g_G(\lambda_M) + \lambda_M]$, which is the same as their utilities when there were no green bonds.

In this case, the utility function for green investors investing in green bonds can be written as:

$$U_{GI}^{GB} = \theta k^{GB} I - I + bI \tag{3.18}$$

Therefore, in the presence of green bonds, firms with λ satisfying

$$bI - c \geq \alpha I[\,\lambda + \sum_{i\in\{G,NG\}} g_i(\lambda)\,] \quad or \quad \lambda + \sum_{i\in\{G,NG\}} g_i(\lambda) \leq \frac{bI-c}{\alpha I} \tag{3.19}$$

would like to issue green bonds. That is, only those relatively less green firms would prefer to issue green bonds. Suppose that Equation (3.19) holds even for some green firms. In other words, there exists a $\lambda_G > 0$ such that $g_G(\lambda_G) + \lambda_G = \frac{bI-c}{\alpha I}$. Additionally, suppose that $\alpha I[g_G(-\rho) - \rho] \geq \theta(X_{NG} - X_G)$, so that all financially constrained non-green firms would prefer green-investor financing in the absence of green bonds (although they face commitment issues and cannot secure green investor financing). Therefore, all firms with $\lambda < \lambda_G$ would prefer to issue green bonds if they can be financed by green investors. As a result, the existence of green bonds increases the demand for green capital.[7]

However, with insufficient green capital, not all firms can be financed by green investors. With green bonds, all issuers provide green investors the same level of utility for a given k (as shown in Equation (3.18)). Assume green investors randomly allocate their capital across firms when they are indifferent. Note that green firms with $\lambda > \lambda_G$ can always secure financing from green investors without issuing green bonds because, for a fixed k, such firms can always offer green investors a higher utility than any green bond issuers. Therefore, only $I_G - (1 - \lambda_G)I$ green capital remains for all green bond issuers.

Consider the case where $\lambda_G I + (1-\rho)I < I_G - (1-\lambda_G)I < \lambda_G I + I$, or $(2-\rho)I < I_G < 2I$. This means the remaining green capital is sufficient for financing the remaining green firms and the non-financially constrained non-green firms, but not sufficient for financing all remaining firms. Therefore, since firms need to

[7] In the absence of green bonds, firms with $\lambda + \sum_{i\in G,NG} g_i(\lambda) < 0$ do not seek green-investor financing.

implement green projects if they finance by issuing green bonds, with scarce green capital, issuing green bonds may risk incurring additional costs (both issuing costs and foregone higher NPV from non-green projects) without securing a lower financial cost if the green bond is not purchased by green investors. Suppose with probability p, a green bond will be purchased by green investors, and with probability $1-p$, the green bond will be purchased by non-green investors who attach no additional value to a green bond. Under this condition, financially constrained non-green firms will issue green bonds if the expected utility from issuing green bonds is greater than what they would obtain from financing without a green bond through non-green investors. That is:

$$p(\theta X_G - \theta k^{GB} I) + (1-p)(\theta X_G - I) + A - c \geq \theta X_{NG} - I + A$$

$$or \quad k^{GB} \leq \frac{1}{\theta} - \frac{c}{\theta I p} - \frac{X_{NG} - X_G}{pI} \tag{3.20}$$

The IC for green firms with $\lambda < \lambda_G$ and the $1-\rho$ non-financially constrained non-green firms is given as:

$$p(\theta X_G - \theta k^{GB} I) + (1-p)(\theta X_G - I) - c \geq \theta X_G - I$$

$$or \quad k^{GB} \leq \frac{1}{\theta} - \frac{c}{\theta I p} \tag{3.21}$$

Both (3.20) and (3.21) are more binding compared to (3.12) and (3.13) respectively, due to the fact that $p \leq 1$. Intuitively, this is because, for the same cost c, issuers now face the risk of their green bonds not being purchased by green investors who attach additional value to green bonds. Therefore, the maximum k they can accept needs to be lower to compensate for this risk. Furthermore, for the same p and c, Equation (3.20) is more binding than (3.21) because financially constrained non-green firms require a sufficiently low financial cost to compensate for foregoing the higher NPV non-green projects. Therefore, green firms and non-constrained firms can increase k^{GB} to (or just above) $\frac{1}{\theta} - \frac{c}{\theta I p} - \frac{X_{NG}-X_G}{pI}$ (with $p = \frac{I_G - (1-\lambda_G)I}{(1+\lambda_G)I} \equiv p_0$) instead of the maximum k in (3.12), which is larger than the one in (3.20). By doing so, they can all secure finance from green investors, given such k also satisfies the green investors' participation constraint:

$$\theta I(\frac{1}{\theta} - \frac{c}{\theta I p} - \frac{X_{NG} - X_G}{pI}) - I + bI \geq 0 \quad or \quad b \geq \frac{c}{pI} + \frac{\theta(X_{NG} - X_G)}{pI} \tag{3.22}$$

If Equation (3.22) holds with p_0,[8] all green firms and financially unconstrained non-green firms can outcompete all financially constrained non-green firms and have their green bonds invested in by green investors with certainty at (or slightly above) $k_0^{GB} = \frac{1}{\theta} - \frac{c}{\theta I p_0} - \frac{X_{NG}-X_G}{I p_0}$ first, and obtain ex post a utility of $U_0^{GB} = \theta X_G - I + \frac{c}{p_0} + \frac{\theta(X_{NG}-X_G)}{p_0} - c + A$ from using green bonds to finance green projects.[9] The financially constrained non-green firms will then compete for the rest of the green capital if there is any. Their IC is still given by (3.20) except that p decreases to $p_1 \equiv \frac{I_G-(2-\rho)I}{\rho I}$.[10] If Equation (3.22) still holds with p_1, then they will set $k_1^{GB} = \frac{1}{\theta} - \frac{c}{\theta I p_1} - \frac{X_{NG}-X_G}{I p_1} < k_0^{GB}$. Ex post, a random p_1 proportion of the ρ financially constrained non-green firms will have their green bonds purchased by green investors and will realize a utility of $U_1^{GB} = \theta X_G - I + \frac{c}{p_1} + \frac{\theta(X_{NG}-X_G)}{p_1} - c + A$; while $1 - p_1$ of the ρ firms will have their green bonds purchased by non-green investors at $k_{NGI}^{GB} = \frac{1}{\theta}$ and will realize a utility of $U_{NGI}^{GB} = \theta X_G - I - c + A$[11].

If Equation (3.22) does not hold with p_1 but holds with p_0, then green investors cannot break even with the maximum gross returns that financially constrained non-green firms can offer. In this case, financially constrained non-green firms will not issue green bonds and will choose non-green projects with non-green investor financing, while the remaining green firms and financially unconstrained non-green firms will have their green bonds invested in by green investors at k_0^{GB}. If Equation (3.22) does not hold even with p_0, financially constrained non-

[8]Note that Equation (3.22) might not hold. The assumptions $g_G(\lambda_G) + \lambda_G = \frac{bI-c}{\alpha I}$ for $\lambda_G > 0$ and $\alpha I[g_G(-\rho) - \rho] \geq \theta(X_{NG} - X_G)$ above only ensure that $bI - c > \theta(X_{NG} - X_G)$; while Equation (3.22) requires $bI - \frac{c}{p} \geq \frac{\theta(X_{NG}-X_G)}{p}$, which is more binding.

[9]The ex ante expected utility is given by the left-hand side of the first line in Equation (3.20).

[10]$p_1 < p_0$ as p_1 is derived from deducting $\lambda_G I + (1-\rho)I$ from both the numerator and the denominator of p_0

[11]The ex ante expected utility of financially constrained non-green firms is $\theta X_{NG} - I$.

green firms will not compete for the scarce green capital. In this scenario, green capital is sufficient for the remaining firms, and they can all secure financing with $k^{GB} = \frac{1-b}{\theta}$, the break-even gross return for green investors investing in green bonds.

Now, compare this to the scenario when there are no green bonds. The scarcity of green capital suggests that only the greenest firms can secure financing from green investors when there are no green bonds. However, with the existence of green bonds distracting green investors from focusing on the overall greenness of a firm, only the relatively less green firms will issue green bonds to try to attract the remaining green capital after the greenest firms have obtained investment. Whether green bonds can help improve the greenness of the economy depends on the level of greenness of the financially constrained firms. As long as those financially constrained firms are not those green firms that could anyway attract green capital in the absence of green bonds, the existence of green bonds can still help improve the greenness of the economy by enabling financially constrained non-green firms to credibly invest in green projects. However, given that these financially constrained firms face a more binding IC, they cannot compete with other non-constrained firms. As a result, while green bonds may still help by acting as a commitment device, this assistance might be limited.[12]

3.3 Empirical Implications and Tests

Section 3.2 demonstrates that under certain circumstances, green bonds could positively contribute to the environment. Although the exact outcomes depend on specific assumptions and parameters, one key feature is consistent across all model variants discussed: green bonds are used by financially constrained firms as a commitment device. This prerequisite is also intuitive. If green bond issuers are investing in green projects they would undertake regardless of the existence of

[12] However, if non-green investors also derive additional utility from green bonds, then the results would be similar to the baseline model, except that the extra utility all investors get in this case is bI.

green bonds, then green bonds will have no impact. However, if green bonds lead firms to undertake actions they would not otherwise consider, then their existence can make a significant difference. Note that this does not require green bonds to offer lower financing costs for the issuers. As long as green bonds can be used as a commitment device that allows financially constrained firms to invest in greener but less profitable projects, they can have a positive environmental impact on the economy. The lower financing costs come from green investors rather than green bonds. Therefore, identifying financially constrained green bond issuers in practice would provide supportive evidence of green bonds' positive impacts. Consequently, my goal here is to empirically test whether there are any green bond issuers facing financial constraints.

3.3.1 Measure of Financial Constraints

Empirically testing or measuring financial constraints has always been challenging, particularly with accounting variables, as many of these variables are endogenous (Farre-Mensa and Ljungqvist, 2016). Ideally, one would use exogenous shocks to firms' available financial resources to identify which firms are financially constrained based on their reactions (e.g. Xu and Kim, 2020; Chaney et al., 2012). However, such events are relatively rare and especially hard to find for an international sample. Another approach, supported by a rich body of literature, is to measure firms' financial constraints using text-based analysis (e.g. Kaplan and Zingales, 1997; Hadlock and Pierce, 2010; Hoberg and Maksimovic, 2015; Buehlmaier and Whited, 2018).

To empirically test whether green bond issuers are financially constrained, I adopt the measure of financial constraint from Hadlock and Pierce (2010). Starting with text-based analysis, Hadlock and Pierce (2010) use an ordered logit model and find that a nonlinear combination of firm age and size can predict how financially constrained a firm is. Using the coefficients from their model, they construct a size-age (SA) index[13] to measure firms' constraint levels, with a higher index value indicating more financial constraint. The SA index is chosen due to its relatively robust performance demonstrated by other researchers (Hoberg and Maksimovic, 2015) and its ease of construction. Unlike Bartram et al. (2021), who categorize firms as financially constrained if their index value is above the sample median, I use the SA index value calculated directly using the formula from Hadlock and Pierce (2010). Thus, the financial constraint level of firms varies continuously. This approach avoids assigning a constraint tag based on an arbitrary cutoff, though it is not captured by the models in the previous sections.

3.3.2 Data

The data used for the empirical analysis comes from three sources: corporate green bond data from Bloomberg's fixed income datab3.Ase, ESG data from Thomson Reuters' Refinitiv Eikon datab3.Ase, and firms' financial data from the Compustat Global and North America datab3.Ases.

Green Bond Data

To obtain a sample of corporate green bonds from Bloomberg, I follow a similar filtering criterion used in Flammer (2021). Specifically, a bond is selected as a green bond if it includes "Green Bond/Loan" in the "Use of Proceeds" field. Bonds with BICS 1 (Bloomberg Industry Classification System Level 1) equal to "Government" are excluded. This yields a sample of 3,000 corporate green bonds with issue dates between January 1, 2013, and May 26, 2021.[14] Table 3.1 shows the summary statistics of selected variables for the resulting sample. The average issuance amount across 2,985 bonds with this information available

[13] The index is calculated as $(-0.737 * Size) + (0.043 * Size^2) - (0.040 * Age)$, where $Size$ is the log of inflation-adjusted book assets, and age is the number of years the firm has been on Compustat with a non-missing stock price. Here, I use the years since the firm went IPO to calculate age instead.

[14] Since the first corporate green bonds were issued in 2013, any bonds issued before that year are excluded.

is \$0.24 billion, which is of the same magnitude as the average issuance amount reported by Flammer (2021). The average maturity for these green bonds is around 9 years, although the maximum maturity can be as long as 1,000 years.[15] Among the 2,649 green bonds with information on external reviews, 83.8% have external reviews. This suggests that seeking third-party review has become a common practice in the green bond market.

Table 3.1: Summary Statistics for Corporate Green Bonds

Statistic	N	Mean	St. Dev.	Min	Max
Ammount (\$Billion)	2,985	0.240	0.356	0.00001	4.330
Yield at Issue (%)	964	2.533	2.343	−0.280	15.000
Coupon (%)	2,873	2.696	2.339	−0.260	16.919
Maturity (Years)	2,949	9.020	41.379	0.159	1,000.663
Bloomberg Rating	665	BBB+		CCC+	AAA
With External Reviews	2,649	0.838	0.368		
Refinance Purpose	3,000	0.126	0.332		

In Table 3.2 and Table 3.3, I summarize the green bond issuance by year and by BICS1 sector, respectively. Table 3.2 shows that the corporate green bond market has been rapidly increasing in size. The total amount issued has surged from \$3.9 billion in 2013 to \$162.3 billion by 2020. The total amount issued by May 26, 2021, has already reached \$127.5 billion. There are a total of 1,601 issuer-year observations in the sample. After removing repeated issuers, 1,079 unique issuers remain across the entire sample period. Table 3.3 reveals that the financial sector has the most green bond issuers and also the highest number of green bonds issued, measured by both the number of issuances and the amount of issuance. Firms in the utilities sector also rank high in all measures.

[15] European Energy A/S has issued a green bond that matures in the year 3020.

Table 3.2: Corporate Green Bond Issuance by Year

Year	Number of Bonds	With External Reviews	Amount Issued ($Billion)	Refinance Purpose	All Issuers	New Issuers	Repeated Issuers
2013	15	3	3.965	0	6	6	0
2014	72	59	14.048	5	34	31	3
2015	202	58	20.934	9	47	38	9
2016	152	115	60.789	14	85	67	18
2017	316	254	79.080	40	164	127	37
2018	409	316	92.975	51	225	165	60
2019	602	497	154.383	75	359	245	114
2020	707	606	162.307	108	380	233	147
2021*	525	313	127.478	76	301	167	134
Total*	3000	2221	715.959	378	1601**	1079	522

**As of May 26th, 2021*

***The sum of All Issuers is the total number of issuer-year. The total number of unique issuers is 1079*

Table 3.3: Corporate Green Bond Issuance by Sector

Sector (BICS1*)	Number of Issuers	Number of Bonds	With External Reviews	Amount Issued ($Billion)
Financials	525	1620	1336	372.107
Utilities	236	607	423	191.563
Energy	70	315	120	24.195
Industrials	100	188	148	45.913
Consumer Discretionary	58	126	73	33.822
Materials	39	70	57	19.771
Consumer Staples	21	27	22	5.939
Technology	14	27	25	11.802
Communications	12	14	13	8.917
Health Care	4	6	4	1.930
Total**	1079	3000	2221	715.959

**Bloomberg Industry Classification Systems Level 1*

***As of May 26th, 2021*

In Appendix C.1, I also report the results by sub-sector (BICS2). Table C.1.2 shows that banks are the top issuers of green bonds. The fact that the financial sector is the top issuer of green bonds may cast doubt on how green bonds contribute to the environment, given that many green bond issuers are intermediaries. Unfortunately, this question will be left unanswered here, as addressing it might require a completely different theoretical model and detailed bank lending data that is usually hard to access. Tables C.1.1 to C.1.5 in the Appendix also include other summary statistics for the green bond sample. One interesting fact is found in Table C.1.1: among issuers with Bloomberg's BNEF clean energy exposure rating, most actually have the lowest rating, indicating they have the least exposure to clean energy. While this does not necessarily mean they are major polluters, it shows that they are, at best, neutral.

ESG and Compustat Data

The ESG data is obtained from the Refinitiv Eikon datab3.Ase, which is one of the major ESG datab3.Ases used in similar analyses. The Refinitiv ESG datab3.Ase provides ESG scores, three pillar scores, and the variables used to calculate those scores for firms with relevant data. Since the focus here is on firms' environmental performance, I selected only the scores and variables related to the environment. Selected variables and their definitions can be found in Table C.2.6 in Appendix C.2. I downloaded the selected variables for all firms in the Refinitiv ESG datab3.Ase from 2006 to 2020. This resulted in 128,415 firm-year observations and 8,561 unique firms. Firms in this sample that have never issued green bonds will be used as a comparison group later on in Section 3.3.3.

To obtain financial data from Compustat, I created a list of firms that is a union of the 8,561 Eikon firms and 1,079 unique green bond issuers. Since Bloomberg does not share the same firm identifier with Compustat, I first obtained the names and IDs of all firms in Compustat, and then fuzzy matched Compustat firm names with Bloomberg issuer names using a fuzzy matching algorithm in R.[16] I then used the IDs of the matched firms to obtain financial data from Compustat North America and Global.

[16]The Levenshtein edit distance is used as the measure of similarity in this case.

3.3.3 Empirical Results

Financial Constraint

To test whether green bond issuers are more financially constrained than non-issuers, I merged the Bloomberg green bond data and Compustat data with the Eikon ESG data by firm and year. I then filtered out all firms in the financial sector, as the original SA index also excluded firms in the financial sector. For the remaining firms with relevant variables available, I calculated the SA index. Table 3.4 summarizes the SA index and environmental information for issuers and non-issuers that are not in the financial sector. The results show that the firm-year average SA index is lower for issuers than for non-issuers, suggesting that, on average, issuers are less financially constrained than non-issuers. In terms of environmental performance, green bond issuers score higher on almost all measures compared to non-issuers. Therefore, on average, green bond issuers appear to be greener and less financially constrained.

Table 3.4: Summary Statistics for Issuers and Non-Issuers

	Issuer		Non-Issuer	
Statistics	N*	Mean	N*	Mean
SA Index	870	−3.0	31,955	−1.1
ESG Score	2,977	56.6	57,455	41.1
Environmental Pillar Score	2,977	55.7	57,446	31.4
Environmental Products	2,977	0.6	57,455	0.3
Eco-Design Products	2,977	0.1	57,454	0.1
Renewable Energy Products	2,977	0.4	57,455	0.1
Sustainable Building Products	2,977	0.1	57,455	0.04
Scope 1 and 2 CO2 (MT)	2,219	5.5	25,871	4.1
Scope 1 and 2 to Rev (T/M$)	2,219	378.0	25,788	486.3
All Scope CO2 (MT)	1,472	10.1	12,090	16.4
All Scope to Rev (T/M$)	1,472	428.9	11,992	1,142.9
Environmental R&D Exp (M$)	351	200.5	2,248	114.0
Percentage of Green Products	23	50.0	123	41.0
Environmental Controversies	12	1.2	88	2.0
Environmental Asset Under Mgt	2,977	0.2	57,455	0.02
Environmental Project Financing	2,977	0.3	57,454	0.03
Fossil Fuel Divestment Policy	2,977	0.02	57,455	0.001

**N is the number of firm-year*

To gain a better understanding of the distribution of both financial constraints and environmental performance for issuers and non-issuers, I plotted the SA Index for issuers and non-issuers by year, as shown in Figure 3.1. It can be seen that green bond issuers not only have a lower median SA Index (represented by the thick line in the middle of each box) across all years, but their SA index is also less dispersed. This is especially evident when we look at the outliers (represented by the dots above the "whiskers" of each box, defined as 1.5 times the interquartile range above the upper quartile or below the lower quartile). Non-issuers have significantly more outliers with much higher SA Index values, indicating that there are many more firms among non-issuers that tend to be very financially constrained. This observation holds across all years. The regression results in Table C.3.7 in Appendix C.3 also support this observation. Column (1) of Table C.3.7 results from regressing the SA index on a binary indicator of whether a firm has ever issued green bonds, while controlling for time fixed effects. The coefficient on the binary indicator is -2.054 and is statistically significant, indicating that green bond issuers, on average, have an SA index that is 2.054 points lower. This suggests that, on average, they are less financially constrained.

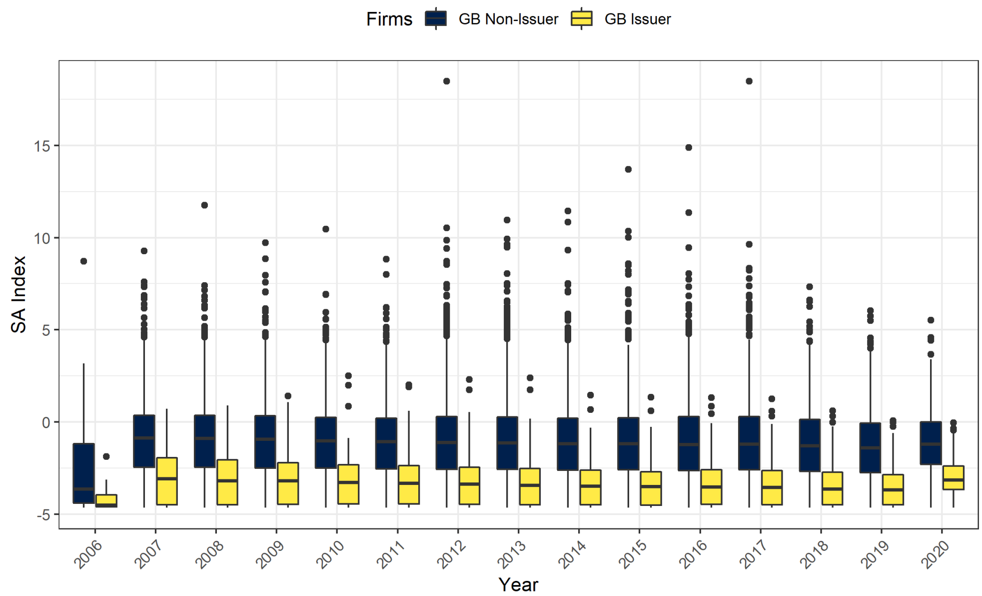


Figure 3.1: Distribution of SA Index for Issuers and Non-Issuers by Year

I also created a similar graph, this time using the environmental pillar score as the Y variable while still excluding firms in the financial sector. It is interesting to see that most issuers have higher E-scores than non-issuers, except for a few outliers. The observations from Figures 3.1 and 3.2 suggest that green bond issuers tend to be greener and less financially constrained firms. In this case, green bonds appear to be used by relatively green firms to finance projects they could finance even without green bonds, rather than as a commitment device for financially constrained firms to pursue green projects they would otherwise be unable to undertake. This contradicts the argument that green bonds significantly contribute to the environment.

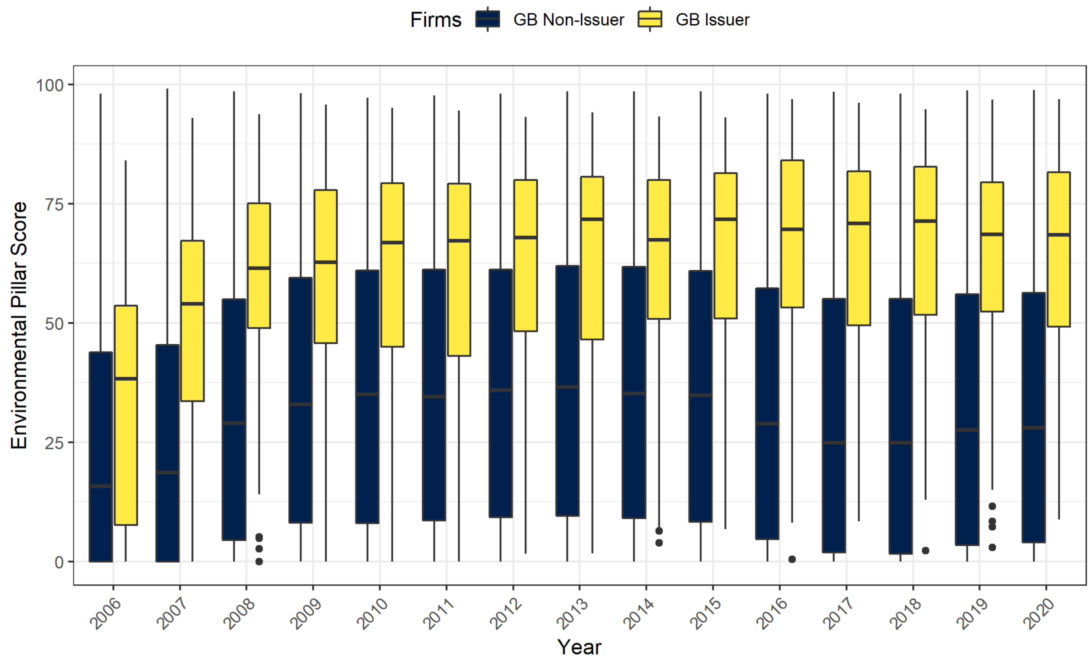


Figure 3.2: Distribution of Environmental Score for Issuers and Non-Issuers by Year

However, it is possible that although green bond issuers are, on average, less financially constrained compared to non-issuers, they might issue green bonds when they are more constrained relative to their own past financial status. Since the SA Index is constructed to be relatively stable over time, it is best used for cross-sectional comparisons and not suitable for time-series analysis. Therefore, I adopt another popular measure of financial constraint, cash flow (e.g. Whited and

Wu, 2006). I regress a binary variable indicating whether an issuer has issued green bonds in a given year on the firm's cash flow lagged by one year, while controlling for year and firm fixed effects. The results are shown in Table 3.5. Column (1) is at the issuer level, while column (2) is at the CAST parent level.[17] I also include issuers that do not have their CAST parents matched in Compustat, making the sample in column (2) slightly larger. Both columns suggest a small but significant positive relationship between the previous year's cash flow and green bond issuance in the subsequent year. In other words, firms tend to issue green bonds when their previous year's cash flow is high, or when they are less financially constrained.

Table 3.5: Green Bond Issuance and Cash Flow

	Dependent Variable: Whether Issue This Year	
	(1)	(2)
Previous Year Cash Flow	0.00001***	0.00001***
	(0.00000)	(0.00000)
F Statistic	66.99***	41.068***
Degree of Freedom (df1; df2)	(1; 14)	(1; 29)
Observations	166	360
R^2	0.057	0.011
Adjusted R^2	-0.135	-0.124
Note:		*p<0.1; **p<0.05; ***p<0.01

All the evidence above suggests that green bond issuers tend to be firms that are less financially constrained, and they also appear to be relatively less constrained when they issue green bonds compared to their own past financial status. Furthermore, the fact that green bond issuers are, on average, greener than non-issuers indicates a negative relationship between financial constraints and environmental scores. The regression of environmental scores on the SA index in Table C.3.8 column (4) in Appendix C.3 confirms this. The coefficient on the SA index is

[17] CAST parent is a variable in Bloomberg, defined as the ultimate parent of a company for capital structure, excluding private shareholders, majority shareholders that own the operating company as an investment, and sovereign owners for government-owned entities where less than 50% of Group debt is guaranteed by the sovereign.

negative and significant, suggesting that firms with higher SA index values (indicating higher levels of financial constraint) tend to have lower environmental scores. From the models derived in Section 3.2, the fact that more financially constrained firms do not issue green bonds and tend to be less green could be due to them being priced out of the green bond market or being too environmentally unfriendly to secure green investor financing, even in the absence of green bonds. The exact scenario depends on how green investors derive non-financial utility from green bonds. If green investors derive utility from green bonds in the manner assumed in Section 3.2.5, i.e., independent of the firms' level of greenness, then it suggests that financially constrained firms have been priced out of the green bond market due to scarce green capital and their more restrictive IC. If this is the case, then in the future, when there is more green capital available, green bonds could incentivize these firms to choose greener projects, thus having a positive environmental impact.

Pricing Premium

To test how investors derive utility from green bonds, first consider that if green investors derive utility from green bonds independent of the firms' level of greenness, the results in Section 3.2.5 suggest that with the supply of green capital being less than the demand, only a random proportion of green bond issuers will benefit from a lower k (i.e., have a pricing premium), and this pricing premium will not depend on the firms' level of greenness. However, if the utility investors derive depends on the firms' level of greenness, then the pricing premium should be larger for greener firms.

Many previous papers on green bonds have focused on identifying a pricing premium, particularly for municipal green bonds (e.g. Baker et al., 2018; Zerbib, 2019; Larcker and Watts, 2020). However, the findings are mixed. Among these papers, Larcker and Watts (2020), by matching green municipal bonds with their non-green counterparts, convincingly found no pricing premium. Flammer (2021) conducted a similar analysis for corporate green bonds and also found no pricing premium. In this study, I conduct the same analysis as Flammer (2021). Following their matching method, I obtained a total of 256 pairs of matched bonds. Unlike municipal bonds, most corporate green bonds do not have "brown twins" (i.e., identical non-green counterparts). Therefore, I keep the closest "brown sibling" of a green bond if both its issue date and maturity date are within one year of the green bond, provided they are from the same issuer and have the same years to maturity.

The t-test result is shown in Figure 3.3. After excluding the matched pairs with issue dates and maturity dates more than one year apart, 236 matched pairs remain. The pricing premium, measured in percentage, is calculated as $\Delta Yield$ = Yield(Nongreen Bond) − Yield(Green Bond), with a positive value indicating a pricing premium. The red dashed line in Figure 3.3 represents the average green premium over the 236 matched pairs, while the blue dashed line marks zero. Consistent with the findings in Flammer (2021), there is no significant pricing premium for green bonds. In fact, the pricing premiums for most green bonds are concentrated around zero, as shown by the vertical bars on the premium axis. Figures C.4.1 to C.4.4 in Appendix C.4 display the results for matched pairs with closer issue and maturity dates. None of these figures suggest any significant pricing premium. However, as the matching criteria become stricter, the dispersion of pricing premiums decreases. In Figure C.4.4, with the distance between dates no more than one month, pricing premiums are closely spread around zero.

Tables C.4.9 to C.4.12 show the t-test results for the pricing premium across different variables for matched pairs with date differences of two quarters or less. Almost all results indicate no significant pricing premium, except for green bonds issued in JPY in Table C.4.11, which on average have a 0.056% yield difference between the matched non-green bond and green bond, and this difference is statistically significant. However, since the number of matched pairs becomes very small when analyzed by categories, the results are not robust.

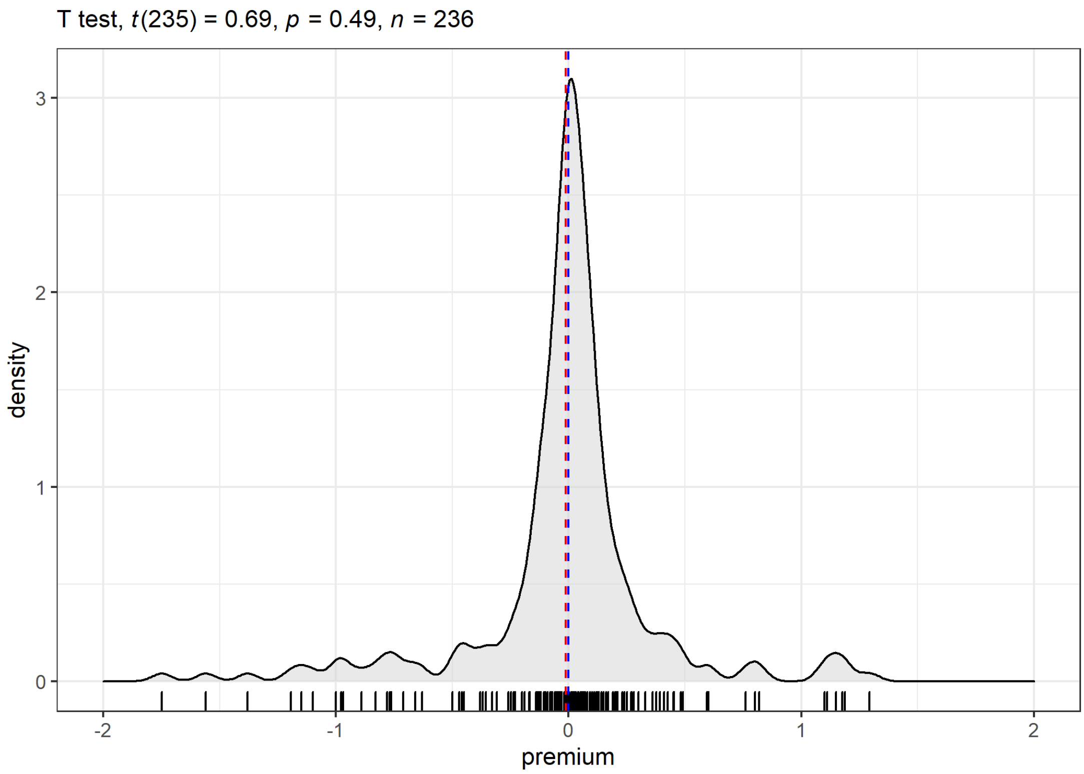


Figure 3.3: T-Test Result for Pricing Premium

Lastly, I conduct a simple regression of the pricing premium on the environmental pillar score of the bond issuer to see if there is any significant relationship. Since not all issuers have an environmental pillar score, the sample size for this analysis is rather small. To avoid the sample being too small, I allowed the date difference between the pairs to be one year or less, but the resulting sample still only includes 38 bonds. The result is shown in Figure 3.4. There is a positive but statistically insignificant relationship between the premium of the bonds and their environmental pillar score. This provides suggestive evidence that investors might derive utility based on firms' level of greenness rather than simply from holding green bonds. Nonetheless, given the small sample size, it is difficult to draw any definitive conclusions.

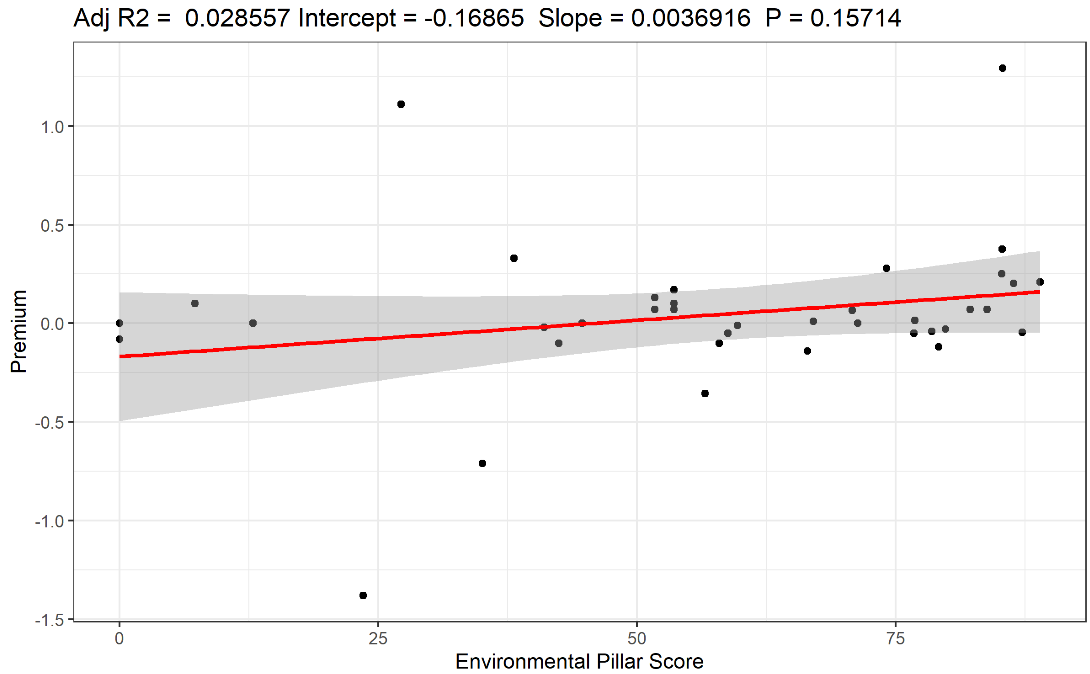


Figure 3.4: Pricing Premium and Environmental Pillar Score

3.4 Conclusion

In this paper, I use a straightforward theoretical framework to identify the conditions under which green bonds could positively impact the environment. Specifically, I demonstrate that a necessary condition for green bonds to have a positive impact is the presence of financially constrained firms using green bonds as a commitment device. This allows them to credibly invest in greener but less profitable projects. To empirically test this, I calculated the SA index as a measure of financial constraint for both green bond issuers and non-issuers with available ESG and financial data. The empirical results suggest that, currently, most green bond issuers are relatively greener and less financially constrained, and thus are less likely to need to use green bonds as a commitment device. Therefore, in the current corporate green bond market, green bonds do not appear to significantly impact the environment by enabling financially constrained firms to undertake green projects that they otherwise would not pursue.

However, there are several limitations to this study. First, the models derived here are based on assumptions that have not yet been empirically verified. Consequently, the model only indicates that green bonds could contribute to the environment under specific conditions. Second, the model developed here is more suitable for studying cases where green bond issuers are financing their own green projects. Given that many green bond issuers are financial intermediaries who use the proceeds to invest in green projects, it may be necessary to derive a separate model for issuers in this category. Third, the measures of financial constraint used in this study are proxies and may not capture the true financial constraints of firms. For more robust empirical results, it would be beneficial to use other measures of financial constraint, preferably those resulting from natural experiments, rather than relying solely on the SA index. Additionally, while the analysis provides suggestive evidence that investors might derive utility based on firms' level of greenness rather than simply from green bonds, the small sample size limits the strength of these conclusions. Further research with larger and more diverse datasets is needed to better understand the relationship between financial constraints, green bond issuance, and environmental impact.

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Appendix A

Appendix For Chapter 1

A.1 Appendix 1.A

Figure A.1.1: The Development of the EU ETS Legislative Framework

	Phase 1 (2005 – 2007)	Phase 2 (2008 – 2012)	Phase 3 (2013 – 2020)	Phase 4 (2021 – 2030)
Geography	EU27	EU27 + Norway, Iceland, Liechtenstein	EU27 (incl. UK) + Norway, Iceland, Liechtenstein Croatia from 1.1.2013 (its aviation from 1.1.2014)	EU27 + Norway, Iceland, Liechtenstein (UK ETS for UK from 1.1.2021)
Sector	Power stations and other combustion plants ≥20MW; oil refineries; coke ovens; iron and steel plants; cement clinker; glass; lime; bricks; ceramics; pulp; paper and board	Same as Phase 1 + aviation (from 2012 for flights within the EEA)	Same as Phase 2 + Aluminium; petrochemical; ammonia; nitric, adipic and glyoxylic acid production; CO_2 capture, transport in pipelines and geological storage of CO2	Same as Phase 3 + An expansion to intra-EEA emissions from the maritime sector from 2023 onward is under discussion
GHGs	CO_2	CO_2, N2O emissions via opt-in	CO_2, N2O, PFC from aluminium production	

The figure presents a table summarizing the development of the EU ETS legislative framework from 2005 onwards. Information is based on the official websites: https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/development-eu-ets-2005-2020_en.

Table A.1.1: Regulated Activities and Corresponding Thresholds Since 2005

Activities and Thresholds
Energy activities
- Combustion installations with a rated thermal input exceeding 20 MW
(except hazardous or municipal waste installations)
- Mineral oil refineries
- Coke ovens
Production and processing of ferrous metals
- Metal ore (including sulphide ore) roasting or sintering installations
- Production of pig iron or steel (primary or secondary fusion) including continuous casting,
with a capacity exceeding 2.5 tonnes per hour
Mineral industry
- Production of cement clinker in rotary kilns with a production capacity exceeding 500 tonnes per day
- Production of lime in rotary kilns or in other furnaces with a production capacity exceeding 50 tonnes per day
- Manufacture of glass including glass fibre with a melting capacity exceeding 20 tonnes per day
- Manufacture of ceramic products by firing, in particular roofing tiles, bricks, refractory bricks, tiles,
stoneware or porcelain, with a production capacity exceeding 75 tonnes per day, and/or with a kiln capacity
exceeding $4m^3$ and with a setting density per kiln exceeding 300 kg/m^3
Other activities
Industrial plants for the production of
(a) pulp from timber or other fibrous materials
(b) paper and board with a production capacity exceeding 20 tonnes per day

The table presents the regulated activities and their respective thresholds as outlined in *ANNEX I of DIRECTIVE 2003/87/EC*, which was initially published in the Official Journal of the European Union on 13 October 2003.

Table A.1.2: Changes and Extensions After 30 June 2011

Extended Activities and Thresholds (Stationary Installation Only)
Metal
- Production and processing of ferrous metals (including ferro-alloys) where combustion units with a total rated thermal input exceeding 20 MW are operated. Processing includes, inter alia, rolling mills, re-heaters, annealing furnaces, smitheries, foundries, coating and pickling
- Production of primary aluminium
- Production of secondary aluminium where combustion units with a total rated thermal input exceeding 20 MW are operated
- Production or processing of non-ferrous metals, including production of alloys, refining, foundry casting, etc., where combustion units with a total rated thermal input (including fuels used as reducing agents) exceeding 20 MW are operated
Mineral industry
- Production of lime or calcination of dolomite or magnesite in rotary kilns or in other furnaces with a production capacity exceeding 50 tonnes per day
- Manufacture of ceramic products by firing, in particular roofing tiles, bricks, refractory bricks, tiles, stoneware or porcelain, with a production capacity exceeding 75 tonnes per day
- Manufacture of mineral wool insulation material using glass, rock or slag with a melting capacity exceeding 20 tonnes per day
- Drying or calcination of gypsum or production of plaster boards and other gypsum products, where combustion units with a total rated thermal input exceeding 20 MW are operated
Other activities
- Production of carbon black involving the carbonisation of organic substances such as oils, tars, cracker and distillation residues, where combustion units with a total rated thermal input exceeding 20 MW are operated
- Production of nitric acid
- Production of adipic acid
- Production of glyoxal and glyoxylic acid
- Production of ammonia
- Production of bulk organic chemicals by cracking, reforming, partial or full oxidation or by similar processes, with a production capacity exceeding 100 tonnes per day
- Production of hydrogen (H_2) and synthesis gas by reforming or partial oxidation with a production capacity exceeding 25 tonnes per day
- Production of soda ash (Na_2CO_3) and sodium bicarbonate ($NaHCO_3$)
- Capture of greenhouse gases from installations covered by this Directive for the purpose of transport and geological storage in a storage site permitted under Directive 2009/31/EC
- Transport of greenhouse gases by pipelines for geological storage in a storage site permitted under Directive 2009/31/EC
- Geological storage of greenhouse gases in a storage site permitted under Directive 2009/31/EC

The table presents the expanded activities and associated thresholds as detailed in *ANNEX I of DIRECTIVE 2003/87/EC*, published in the Official Journal of the European Union in 2013. It includes only those activities that were newly added or modified in comparison to those listed in Table A.1.1 for stationary installations.

A.2 Appendix 1.B

Table A.2.3: Impact of EU ETS on Major Outcomes

	± 2	± 4.2	[-4.2, 7]	[-4.2, 10]	[-4.2, 15]
Scope 1 (Absolute)	-0.913	0.552	0.297	0.052	-0.266
	(0.727)	(0.813)	(1.011)	(0.955)	(0.798)
Scope 1 (Intensity)	-0.736	-0.511	-2.043	-3.058**	-2.884***
	(1.053)	(1.401)	(1.516)	(1.315)	(1.032)
Scope 2 (Absolute)	0.693	1.447*	1.266	3.213***	3.210***
	(0.704)	(0.772)	(1.172)	(1.109)	(0.921)
Scope 1 & 2 (Absolute)	-0.424	0.874	0.708	1.151	1.056
	(0.644)	(0.644)	(0.818)	(0.799)	(0.701)
Scope 1 & 2 (Intensity)	-0.247	0.002	-1.223	-1.654	-1.378
	(1.001)	(1.316)	(1.378)	(1.197)	(0.955)
Revenue	-0.177	1.063	2.341	3.111**	2.618**
	(1.346)	(1.445)	(1.584)	(1.443)	(1.200)
Net Income	0.041	0.051	0.079	0.101**	0.077*
	(0.039)	(0.049)	(0.054)	(0.049)	(0.041)
Capital Expenditure	-1.223	-0.067	0.688	1.511	1.153
	(1.864)	(1.759)	(1.937)	(1.735)	(1.426)
Observations	1058(L) 1121(R)	2161(L) 2349(R)	2161(L) 3657(R)	2161(L) 4761(R)	2161(L) 6379(R)
Polynomial	1	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	Manual	Manual	Manual	Manual	Manual

* p < 0.1, ** p < 0.05, *** p < 0.01

Table A.2.3: Impact of EU ETS on Major Outcomes

	± 2	± 4.2	[-4.2, 7]	[-4.2, 10]	[-4.2, 15]
No. of European Firms	-14.748	-18.605	-24.332	-42.208	-40.259*
	(22.016)	(24.073)	(28.509)	(25.903)	(20.652)
No. of Non-European Firms	0.698	-5.577	-10.968	-27.244	-27.599
	(21.367)	(24.747)	(29.393)	(27.060)	(21.803)
European Firms (Share)	-0.391**	-0.450**	-0.468*	-0.761***	-0.728***
	(0.164)	(0.196)	(0.244)	(0.219)	(0.162)
No. of European Customers	9.082*	4.688	5.924	4.488	6.299
	(5.028)	(5.186)	(5.845)	(5.490)	(4.499)
No. of Non-European Customers	12.292	10.638	9.967	15.254	18.177*
	(9.527)	(10.393)	(12.743)	(12.589)	(10.843)
No. of European Suppliers	-8.405	-4.333	-8.691	-12.427	-10.781
	(11.597)	(13.029)	(15.701)	(14.509)	(12.340)
No. of Non-European Suppliers	-1.573	8.878	4.454	18.950	21.231
	(32.001)	(29.425)	(31.672)	(28.831)	(24.598)
Observations	690(L) 733(R)	1315(L) 1584(R)	1315(L) 2406(R)	1315(L) 3074(R)	1315(L) 4111(R)
European Customers	0.032	-0.097	-0.079	-0.279	-0.248
(Share in Customers)	(0.194)	(0.227)	(0.265)	(0.239)	(0.196)
Observations	596(L) 584(R)	1090(L) 1317(R)	1090(L) 2026(R)	1090(L) 2614(R)	1090(L) 3471(R)
European Suppliers	-0.145	-0.207	-0.213	-0.419**	-0.377**
(Share in Suppliers)	(0.137)	(0.179)	(0.218)	(0.192)	(0.152)
Observations	643(L) 651(R)	1226(L) 1433(R)	1226(L) 2192(R)	1226(L) 2807(R)	1226(L) 3748(R)
Polynomial	1	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	Manual	Manual	Manual	Manual	Manual

* p < 0.1, ** p < 0.05, *** p < 0.01

Table A.2.3: Impact of EU ETS on Major Outcomes

	± 2	± 4.2	[-4.2, 7]	[-4.2, 10]	[-4.2, 15]
No. of Technological Links	-11.805	-1.361	-6.111	-0.874	-1.634
	(14.906)	(13.868)	(16.962)	(16.477)	(13.812)
Technological Links (Share)	-0.085	-0.065	-0.063	0.022	0.037
	(0.077)	(0.079)	(0.098)	(0.095)	(0.079)
No. of Added Technological Links	-2.811	-0.676	-1.176	-0.050	0.491
	(2.900)	(2.783)	(3.693)	(3.694)	(3.188)
No. of Dropped Technological Links	-1.148	-0.125	-1.090	-0.576	-0.680
	(1.724)	(1.646)	(2.074)	(2.013)	(1.665)
No. of License-To Links	-1.485	-0.415	-1.516	1.961	2.558
	(1.504)	(1.682)	(2.917)	(2.949)	(2.421)
No. of License-From Links	-2.584	1.748	0.881	3.975	2.651
	(1.692)	(2.646)	(4.005)	(3.683)	(2.735)
Observations	691(L) 733(R)	1316(L) 1584(R)	1316(L) 2406(R)	1316(L) 3074(R)	1316(L) 4111(R)
License-To Links	0.014	-0.022	-0.082	0.038	0.036
(Share in Tech)	(0.181)	(0.197)	(0.237)	(0.204)	(0.162)
License-From Links	0.016	0.253	0.446	0.609**	0.478***
(Share in Tech)	(0.289)	(0.353)	(0.344)	(0.250)	(0.168)
Observations	491(L) 503(R)	907(L) 1124(R)	907(L) 1716(R)	907(L) 2220(R)	907(L) 2962(R)
Polynomial	1	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	Manual	Manual	Manual	Manual	Manual

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.4: Impact of EU ETS on Major Outcomes (Phase 1)

	± 2	± 4.2	[-4.2, 7]	[-4.2, 10]	[-4.2, 15]
Scope 1 (Absolute)	-0.774	0.529	0.430	0.111	-0.125
	(0.743)	(0.832)	(1.046)	(0.973)	(0.815)
Scope 1 (Intensity)	-0.831	-0.716	-2.061	-3.129**	-2.724**
	(1.321)	(1.517)	(1.633)	(1.404)	(1.109)
Scope 2 (Absolute)	0.366	1.015	0.897	2.274**	2.171**
	(0.667)	(0.797)	(1.107)	(1.078)	(0.950)
Scope 1 & 2 (Absolute)	-0.433	0.573	0.448	0.617	0.599
	(0.682)	(0.692)	(0.854)	(0.816)	(0.715)
Scope 1 & 2 (Intensity)	-0.491	-0.423	-1.480	-2.139	-1.713*
	(1.251)	(1.446)	(1.520)	(1.309)	(1.039)
Revenue	0.058	1.245	2.491	3.240**	2.599**
	(1.431)	(1.502)	(1.621)	(1.465)	(1.215)
Net Income	-0.075	-0.047	-0.008	-0.006	-0.027
	(0.056)	(0.087)	(0.102)	(0.093)	(0.077)
Capital Expenditure	-0.700	0.429	1.393	1.925	1.320
	(2.289)	(2.239)	(2.325)	(1.966)	(1.549)
Observations	198(L) 210(R)	414(L) 441(R)	414(L) 687(R)	414(L) 894(R)	414(L) 1197(R)
Polynomial	1	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	Manual	Manual	Manual	Manual	Manual

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.4: Impact of EU ETS on Major Outcomes (Phase 1)

	± 2	± 4.2	[-4.2, 7]	[-4.2, 10]	[-4.2, 15]
No. of European Firms	-16.966*	-7.891	-9.562	-11.446	-11.942*
	(9.072)	(7.618)	(8.605)	(7.888)	(6.666)
No. of Non-European Firms	-1.619	1.264	0.364	-0.198	-1.004
	(7.195)	(6.659)	(7.670)	(7.202)	(6.278)
European Firms (Share)	-0.622**	-0.456*	-0.607*	-0.845***	-0.821***
	(0.249)	(0.275)	(0.338)	(0.308)	(0.252)
No. of European Customers	2.435	1.315	1.259	1.478	1.347
	(1.984)	(2.072)	(2.375)	(2.394)	(2.177)
No. of Non-European Customers	8.071	6.364	8.736	11.820*	10.475*
	(5.294)	(5.438)	(6.705)	(6.903)	(6.205)
No. of European Suppliers	-6.158	-2.351	-2.610	-3.272	-3.696
	(5.225)	(4.356)	(4.857)	(4.231)	(3.454)
No. of Non-European Suppliers	12.224	18.794	20.172	35.591	30.884*
	(27.686)	(25.574)	(26.864)	(22.335)	(17.284)
Observations	87(L) 80(R)	162(L) 184(R)	162(L) 278(R)	162(L) 361(R)	162(L) 481(R)
European Customers	0.194	-0.003	-0.070	-0.104	-0.043
(Share in Customers)	(0.381)	(0.387)	(0.414)	(0.361)	(0.307)
Observations	68(L) 66(R)	112(L) 149(R)	112(L) 228(R)	112(L) 296(R)	112(L) 383(R)
European Suppliers	-0.551**	-0.392	-0.499	-0.708***	-0.662***
(Share in Suppliers)	(0.276)	(0.278)	(0.321)	(0.252)	(0.187)
Observations	84(L) 74(R)	154(L) 170(R)	154(L) 260(R)	154(L) 338(R)	154(L) 440(R)
Polynomial	1	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	Manual	Manual	Manual	Manual	Manual

* p < 0.1, ** p < 0.05, *** p < 0.01

Table A.2.4: Impact of EU ETS on Major Outcomes (Phase 1)

	± 2	± 4.2	[-4.2, 7]	[-4.2, 10]	[-4.2, 15]
No. of Technological Links	-11.322	0.034	2.236	10.589	6.676
	(7.245)	(7.807)	(12.108)	(11.625)	(9.707)
Technological Links (Share)	-0.139	-0.098	-0.020	0.121	0.124
	(0.110)	(0.154)	(0.203)	(0.187)	(0.157)
No. of Added Technological Links	-2.666**	-0.145	0.340	1.833	1.611
	(1.216)	(1.595)	(2.387)	(2.224)	(1.789)
No. of Dropped Technological Links	-1.062	0.242	0.526	2.087	1.249
	(1.097)	(1.261)	(1.834)	(1.652)	(1.330)
No. of License-To Links	-0.903	1.143	0.721	2.519	1.845
	(1.589)	(1.643)	(2.656)	(2.507)	(2.056)
No. of License-From Links	-4.162	1.497	1.366	4.327	1.299
	(2.580)	(3.514)	(4.994)	(4.502)	(3.728)
Observations	87(L) 80(R)	162(L) 184(R)	162(L) 278(R)	162(L) 361(R)	162(L) 481(R)
License-To Links	0.496	0.512	0.433	0.616	0.450
(Share in Tech)	(0.601)	(0.587)	(0.628)	(0.387)	(0.288)
License-From Links	-0.391	0.345	0.926	0.874	0.529
(Share in Tech)	(1.025)	(1.312)	(1.081)	(0.659)	(0.473)
Observations	42(L) 49(R)	77(L) 107(R)	77(L) 161(R)	77(L) 221(R)	77(L) 292(R)
Polynomial	1	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	Manual	Manual	Manual	Manual	Manual

* p < 0.1, ** p < 0.05, *** p < 0.01

Table A.2.5: Impact of EU ETS on Major Outcomes (Phase 2)

	± 2	± 4.2	[-4.2, 7]	[-4.2, 10]	[-4.2, 15]
Scope 1 (Absolute)	-0.931	0.588	0.404	0.163	-0.104
	(0.827)	(0.879)	(1.076)	(1.008)	(0.844)
Scope 1 (Intensity)	-0.823	-0.373	-1.849	-2.887**	-2.652***
	(1.019)	(1.364)	(1.494)	(1.296)	(1.019)
Scope 2 (Absolute)	0.759	1.622**	1.453	3.088***	2.961***
	(0.703)	(0.768)	(1.127)	(1.084)	(0.931)
Scope 1 & 2 (Absolute)	-0.406	0.933	0.764	1.084	0.983
	(0.716)	(0.697)	(0.868)	(0.842)	(0.739)
Scope 1 & 2 (Intensity)	-0.298	0.168	-1.025	-1.608	-1.338
	(0.971)	(1.308)	(1.402)	(1.219)	(0.966)
Revenue	-0.108	0.961	2.252	3.050**	2.548**
	(1.337)	(1.436)	(1.592)	(1.455)	(1.211)
Net Income	-0.032	-0.014	0.005	0.013	-0.007
	(0.040)	(0.064)	(0.076)	(0.070)	(0.059)
Capital Expenditure	-1.399	-0.030	0.610	1.362	0.953
	(1.907)	(1.820)	(2.041)	(1.833)	(1.493)
Observations	330(L) 350(R)	688(L) 735(R)	688(L) 1145(R)	688(L) 1490(R)	688(L) 1995(R)
Polynomial	1	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	Manual	Manual	Manual	Manual	Manual

* p < 0.1, ** p < 0.05, *** p < 0.01

Table A.2.5: Impact of EU ETS on Major Outcomes (Phase 2)

	± 2	± 4.2	[-4.2, 7]	[-4.2, 10]	[-4.2, 15]
No. of European Firms	-13.127	-10.050	-13.889	-21.945*	-23.300**
	(11.848)	(11.689)	(13.358)	(12.010)	(9.496)
No. of Non-European Firms	1.438	0.638	-3.079	-9.892	-12.365
	(10.310)	(11.596)	(13.574)	(12.558)	(10.302)
European Firms (Share)	-0.418**	-0.398*	-0.527**	-0.827***	-0.834***
	(0.179)	(0.211)	(0.267)	(0.244)	(0.186)
No. of European Customers	3.013*	2.848	3.072	3.511	3.274*
	(1.577)	(1.894)	(2.271)	(2.277)	(1.988)
No. of Non-European Customers	8.032	4.449	6.846	11.043	11.127
	(8.071)	(7.166)	(8.086)	(7.939)	(6.869)
No. of European Suppliers	-3.795	-1.856	-3.475	-6.631	-7.419
	(5.632)	(5.866)	(6.894)	(6.153)	(5.091)
No. of Non-European Suppliers	12.458	14.860	15.216	21.650	17.434
	(28.214)	(24.405)	(24.371)	(21.090)	(17.205)
Observations	192(L) 197(R)	354(L) 437(R)	354(L) 664(R)	354(L) 844(R)	354(L) 1128(R)
European Customers	0.109	0.124	0.118	-0.081	-0.083
(Share in Customers)	(0.207)	(0.249)	(0.300)	(0.265)	(0.223)
Observations	148(L) 147(R)	260(L) 337(R)	260(L) 512(R)	260(L) 663(R)	260(L) 879(R)
European Suppliers	-0.169	-0.227	-0.314	-0.546**	-0.515***
(Share in Suppliers)	(0.174)	(0.216)	(0.256)	(0.221)	(0.170)
Observations	169(L) 175(R)	321(L) 397(R)	321(L) 598(R)	321(L) 764(R)	321(L) 1019(R)
Polynomial	1	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	Manual	Manual	Manual	Manual	Manual

* p < 0.1, ** p < 0.05, *** p < 0.01

Table A.2.5: Impact of EU ETS on Major Outcomes (Phase 2)

	± 2	± 4.2	[-4.2, 7]	[-4.2, 10]	[-4.2, 15]
No. of Technological Links	-11.599*	-1.984	-2.426	2.959	-0.254
	(6.963)	(6.500)	(9.343)	(9.156)	(7.605)
Technological Links (%)	-0.180*	-0.138	-0.109	-0.022	-0.021
	(0.099)	(0.108)	(0.137)	(0.133)	(0.114)
No. of Added Technological Links	-1.858	-0.794	-0.896	-0.002	-0.205
	(1.473)	(1.299)	(1.639)	(1.592)	(1.346)
No. of Dropped Technological Links	-1.197	-0.294	-0.172	0.666	0.639
	(0.738)	(0.709)	(1.127)	(1.128)	(0.919)
No. of License-To Links	-1.894	-0.253	-0.842	0.839	0.728
	(1.607)	(1.375)	(2.311)	(2.300)	(1.881)
No. of License-From Links	-3.053	2.150	2.091	4.854	2.093
	(1.983)	(3.105)	(4.521)	(4.102)	(3.230)
Observations	192(L) 197(R)	354(L) 437(R)	354(L) 664(R)	354(L) 844(R)	354(L) 1128(R)
License-To Links	-0.200	-0.368	-0.539	-0.309	-0.199
(% Tech)	(0.391)	(0.333)	(0.365)	(0.329)	(0.273)
License-From Links	0.228	0.655	1.054	1.270***	0.894***
(% Tech)	(0.662)	(0.778)	(0.730)	(0.449)	(0.282)
Observations	121(L) 119(R)	209(L) 271(R)	209(L) 408(R)	209(L) 536(R)	209(L) 713(R)
Polynomial	1	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	Manual	Manual	Manual	Manual	Manual

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.6: Impact of EU ETS on Major Outcomes (Phase 3)

	± 2	± 4.2	[-4.2, 7]	[-4.2, 10]	[-4.2, 15]
Scope 1 (Absolute)	-0.954	0.538	0.181	-0.039	-0.419
	(0.753)	(0.824)	(1.018)	(0.974)	(0.817)
Scope 1 (Intensity)	-0.646	-0.521	-2.160	-3.141**	-3.092***
	(1.053)	(1.424)	(1.535)	(1.343)	(1.059)
Scope 2 (Absolute)	0.773	1.499*	1.288	3.649***	3.756***
	(0.769)	(0.834)	(1.317)	(1.227)	(0.977)
Scope 1 & 2 (Absolute)	-0.432	0.951	0.774	1.398*	1.275*
	(0.676)	(0.665)	(0.848)	(0.833)	(0.729)
Scope 1 & 2 (Intensity)	-0.124	0.056	-1.248	-1.498	-1.276
	(1.007)	(1.323)	(1.366)	(1.197)	(0.967)
Revenue	-0.308	1.059	2.342	3.103**	2.673**
	(1.368)	(1.462)	(1.596)	(1.454)	(1.210)
Net Income	0.116	0.115	0.148	0.185	0.160
	(0.093)	(0.133)	(0.153)	(0.144)	(0.123)
Capital Expenditure	-1.290	-0.217	0.540	1.472	1.211
	(1.762)	(1.656)	(1.833)	(1.667)	(1.391)
Observations	530(L) 561(R)	1108(L) 1177(R)	1108(L) 1834(R)	1108(L) 2386(R)	1108(L) 3196(R)
Polynomial	1	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	Manual	Manual	Manual	Manual	Manual

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.6: Impact of EU ETS on Major Outcomes (Phase 3)

	± 2	± 4.2	[-4.2, 7]	[-4.2, 10]	[-4.2, 15]
No. of European Firms	-14.096	-25.364	-30.445	-57.177	-53.428*
	(32.160)	(34.683)	(41.815)	(38.809)	(30.909)
No. of Non-European Firms	1.763	-10.233	-15.395	-40.353	-39.899
	(31.726)	(35.899)	(43.025)	(40.012)	(31.783)
European Firms (Share)	-0.294	-0.463**	-0.399	-0.692***	-0.639***
	(0.201)	(0.224)	(0.275)	(0.253)	(0.196)
No. of European Customers	14.196*	6.539	8.808	6.227	9.485
	(8.045)	(7.996)	(8.861)	(8.317)	(6.637)
No. of Non-European Customers	15.621	14.730	12.130	18.776	24.323
	(14.433)	(15.080)	(18.424)	(18.144)	(15.165)
No. of European Suppliers	-10.940	-6.275	-12.301	-16.395	-12.971
	(17.723)	(19.548)	(23.359)	(21.803)	(18.414)
No. of Non-European Suppliers	-12.199	3.121	-3.654	15.412	22.666
	(36.761)	(34.915)	(38.989)	(36.552)	(31.527)
Observations	412(L) 456(R)	800(L) 963(R)	800(L) 1464(R)	800(L) 1869(R)	800(L) 2502(R)
European Customers	-0.041	-0.210	-0.160	-0.373	-0.354*
(Share in Customers)	(0.210)	(0.250)	(0.288)	(0.265)	(0.213)
Observations	380(L) 371(R)	718(L) 831(R)	718(L) 1286(R)	718(L) 1655(R)	718(L) 2209(R)
European Suppliers	-0.019	-0.146	-0.107	-0.309	-0.273
(Share in Suppliers)	(0.196)	(0.221)	(0.264)	(0.244)	(0.200)
Observations	390(L) 402(R)	751(L) 866(R)	751(L) 1334(R)	751(L) 1705(R)	751(L) 2289(R)
Polynomial	1	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	Manual	Manual	Manual	Manual	Manual

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.6: Impact of EU ETS on Major Outcomes (Phase 3)

	± 2	± 4.2	[-4.2, 7]	[-4.2, 10]	[-4.2, 15]
No. of Technological Links	-12.938	-1.543	-8.842	-4.926	-4.221
	(23.724)	(22.255)	(26.501)	(25.736)	(21.323)
Technological Links (Share)	-0.025	-0.020	-0.041	0.025	0.043
	(0.094)	(0.091)	(0.106)	(0.102)	(0.084)
No. of Added Technological Links	-3.417	-0.710	-1.427	-0.346	0.627
	(4.588)	(4.429)	(5.879)	(5.928)	(5.046)
No. of Dropped Technological Links	-1.302	-0.218	-1.760	-1.741	-1.764
	(2.819)	(2.700)	(3.263)	(3.140)	(2.561)
No. of License-To Links	-1.423	-0.857	-2.425	2.395	3.763
	(1.833)	(2.170)	(3.694)	(3.782)	(3.095)
No. of License-From Links	-1.981	1.615	0.244	3.442	3.189
	(1.508)	(2.390)	(3.685)	(3.427)	(2.445)
Observations	412(L) 456(R)	800(L) 963(R)	800(L) 1464(R)	800(L) 1869(R)	800(L) 2502(R)
License-To Links	0.042	0.037	0.031	0.111	0.077
(Share in Tech)	(0.220)	(0.226)	(0.244)	(0.209)	(0.160)
License-From Links	-0.032	0.072	0.200	0.356*	0.327***
(Share in Tech)	(0.129)	(0.203)	(0.220)	(0.182)	(0.127)
Observations	328(L) 335(R)	621(L) 746(R)	621(L) 1147(R)	621(L) 1463(R)	621(L) 1957(R)
Polynomial	1	1	1	1	1
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth Type	Manual	Manual	Manual	Manual	Manual

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.3 Appendix 1.C

Table A.3.7: Impact of Regulation Stringency on GHG Emissions

Dependent Variables:	Scope1 (abs)	Scope1 (int)	Scope2 (abs)	Scope 1&2 (abs)	Scope 1&2 (int)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
$\Delta Stringency \times Year = 2013$	-0.0020	-0.0037	-0.0190**	0.0019	0.0003
	(0.0024)	(0.0025)	(0.0081)	(0.0025)	(0.0026)
$\Delta Stringency \times Year = 2014$	-0.0150***	-0.0235***	0.0995***	-0.0111***	-0.0196***
	(0.0026)	(0.0025)	(0.0090)	(0.0027)	(0.0025)
$\Delta Stringency \times Year = 2015$	-0.0196***	-0.0397***	0.1140***	-0.0181***	-0.0382***
	(0.0025)	(0.0031)	(0.0141)	(0.0026)	(0.0032)
Verified Emissions (tCO2e)	-0.0080	-0.0063	0.1114	-0.0031	-0.0014
	(0.0173)	(0.0162)	(0.1482)	(0.0161)	(0.0154)
Regulated Plants (%)	0.0041	-0.0682	0.1060	0.0537	-0.0186
	(0.0675)	(0.0484)	(0.0842)	(0.0582)	(0.0408)
Δ No. of Regulated Plants	-0.0235	-0.0249	0.0119	-0.0264	-0.0278
	(0.0295)	(0.0289)	(0.0322)	(0.0280)	(0.0276)
Disclosure	0.0806	0.0586	0.1073**	0.0470	0.0250
	(0.0941)	(0.0932)	(0.0483)	(0.0692)	(0.0681)
Total Assets ($M)	0.1859***	-0.2301**	-1.978***	0.1320**	-0.2839***
	(0.0569)	(0.0931)	(0.4966)	(0.0539)	(0.0985)
Debt to Equity	-0.0124*	-0.0157***	0.0217***	0.0003	-0.0030
	(0.0068)	(0.0047)	(0.0057)	(0.0076)	(0.0059)
ln Output Capacity (MWe)	2.178***	0.1227	2.350***	2.171***	0.1157
	(0.3228)	(0.1326)	(0.3033)	(0.3215)	(0.1072)
Fixed-effects					
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	2,345	2,345	2,345	2,345	2,345
R^2	0.98914	0.98021	0.98483	0.99133	0.97801
Within R^2	0.08345	0.02855	0.23102	0.08875	0.02650

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents the DID estimates of the impacts of the regulatory stringency change on firms' GHG emissions in logarithmic scale. The unit of all pre-scaled absolute amount of emissions is tonnes of carbon dioxide equivalent, or tCO2e; while the unit of the corresponding carbon intensity is $tCO2e/US\$mnRevenues$, i.e. calculated as dividing the absolute amount of emissions by a firm's annual consolidated revenues in millions of US dollars. All explanatory variables are standardized. The units presented for some variables are those before standardization.

Table A.3.8: Impact of Regulation Stringency on Financials

Dependent Variables:	Revenue	Net Income	Capital Expenditure
Model:	(1)	(2)	(3)
Variables			
$\Delta Stringency \times Year = 2013$	0.0006	0.0023	-0.0029
	(0.0007)	(0.0044)	(0.0018)
$\Delta Stringency \times Year = 2014$	0.0032***	0.0022	0.0066
	(0.0005)	(0.0032)	(0.0056)
$\Delta Stringency \times Year = 2015$	0.0076***	0.0140**	-0.1519***
	(0.0011)	(0.0059)	(0.0148)
Verified Emissions (tCO2e)	-0.0007	0.1422*	0.2164***
	(0.0028)	(0.0849)	(0.0787)
Regulated Plants (%)	0.0273	0.0444	0.0272
	(0.0200)	(0.0329)	(0.0349)
Δ No. of Regulated Plants	0.0005	1.64×10^{-5}	0.0039
	(0.0019)	(0.0182)	(0.0062)
Disclosure	0.0083***	0.0009	0.0114**
	(0.0015)	(0.0060)	(0.0056)
Total Assets ($M)	0.1572***	0.1052	0.0854*
	(0.0445)	(0.1642)	(0.0454)
Debt to Equity	0.0012	-0.0034	0.0008
	(0.0013)	(0.0053)	(0.0059)
ln Output Capacity (MWe)	0.7767***	-0.1006	0.6816***
	(0.1356)	(0.1118)	(0.1647)
Fixed-effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,345	2,345	2,345
R^2	0.99827	0.76929	0.98721
Within R^2	0.27525	0.00384	0.59050

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents the DID estimates of the impacts of regulation stringency on firms' financial performance in logarithmic scale. The unit of all pre-scaled value is millions of US dollars. All variables, including dependent variables are standardized. The units presented for some variables are those before standardization.

Table A.3.9: Impact of Regulation Stringency on Firm Supply Chains

Dependent Variables:	No. of European Firms	European Firms (Share)	No. of European Customers	European Customers (Share in Customers)	No. of European Suppliers	European Suppliers (Share in Suppliers)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\Delta Stringency \times Year = 2013$	0.3530***	-0.0043***	0.3704***	0.0150***	0.1611***	-0.0058***
	(0.0573)	(0.0012)	(0.0356)	(0.0014)	(0.0596)	(0.0014)
$\Delta Stringency \times Year = 2014$	0.0155	-0.0125***	0.0205	0.0111***	0.6148***	-0.0115***
	(0.0505)	(0.0011)	(0.0327)	(0.0013)	(0.0680)	(0.0014)
$\Delta Stringency \times Year = 2015$	0.2875***	-0.0099***	-0.0929**	0.0035**	1.221***	-0.0077***
	(0.0517)	(0.0012)	(0.0429)	(0.0018)	(0.0759)	(0.0014)
Verified Emissions (tCO2e)	0.3695	0.0075	0.2133	0.0056	0.0141	0.0035
	(0.5041)	(0.0102)	(0.2948)	(0.0124)	(0.5593)	(0.0084)
Regulated Plants (%)	-1.669	-0.0044	-0.3406	-0.0014	-1.310	-0.0070
	(1.377)	(0.0150)	(0.5989)	(0.0217)	(0.9756)	(0.0205)
Δ No. of Regulated Plants	0.1843	0.0007	0.1902*	0.0063	-0.0385	-0.0076
	(0.2520)	(0.0034)	(0.1116)	(0.0054)	(0.1508)	(0.0082)
Disclosure	-0.5918**	-0.0003	-0.5083***	-0.0020	-0.2897***	-0.0139**
	(0.2421)	(0.0025)	(0.1079)	(0.0052)	(0.0512)	(0.0062)
Total Assets ($M)	-12.54***	0.0687***	-1.202	0.0299	4.182*	0.1044***
	(1.714)	(0.0239)	(1.101)	(0.0294)	(2.176)	(0.0301)
Debt to Equity	0.0882	-0.0018	0.1439***	0.0050	-0.0632	-0.0052
	(0.0778)	(0.0033)	(0.0499)	(0.0033)	(0.0631)	(0.0041)
ln Output Capacity (MWe)	2.757	0.0664	-0.6823	0.0524	2.331	0.0376
	(3.231)	(0.0791)	(1.788)	(0.1161)	(1.628)	(0.0521)
Number of Links	29.38***	-0.0263**	3.677***	-0.0315***	20.23***	-0.0433***
	(0.7681)	(0.0107)	(0.4644)	(0.0103)	(0.5622)	(0.0130)
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,169	2,169	2,169	2,015	2,169	2,122
R^2	0.99250	0.89874	0.86795	0.90703	0.98956	0.86857
Within R^2	0.82046	0.03519	0.11366	0.02697	0.72612	0.05003

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents the DID estimates of the impacts of regulation stringency on the geographic distribution of regulated firms' supply chains. All explanatory variables are standardized. The units presented for some variables are those before standardization.

Table A.3.10: Impact of Regulation Stringency on Technological Network (1)

Dependent Variables:	No. of Technology Links	Technology Links (Share)	No. of Added Technology Links	No. of Dropped Technology Links
Model:	(1)	(2)	(3)	(4)
Variables				
$\Delta Stringency \times Year = 2013$	0.7498***	0.0046***	0.7210***	0.4665***
	(0.1587)	(0.0015)	(0.0644)	(0.0383)
$\Delta Stringency \times Year = 2014$	0.0480	0.0004	-0.2897***	0.1719***
	(0.0934)	(0.0012)	(0.0616)	(0.0195)
$\Delta Stringency \times Year = 2015$	-0.3010*	-0.0007	0.2152***	0.7876***
	(0.1616)	(0.0013)	(0.0541)	(0.0276)
Verified Emissions (tCO2e)	0.7986	0.0040	-0.2126	0.4192
	(0.6699)	(0.0060)	(0.6354)	(0.5373)
Regulated Plants (%)	-3.299	-0.0100	-1.317*	0.0632
	(2.770)	(0.0140)	(0.7533)	(0.3531)
Δ No. of Regulated Plants	-0.0533	0.0005	0.1268	0.0708
	(0.5551)	(0.0028)	(0.1194)	(0.0448)
Disclosure	-0.0132	-0.0029	-0.0051	-0.0059
	(0.2652)	(0.0058)	(0.1006)	(0.0362)
Total Assets ($M)	-27.68***	-0.2297***	-5.436***	-0.5094
	(8.278)	(0.0617)	(1.770)	(0.4064)
Debt to Equity	0.1467	0.0006	0.0503	0.0104
	(0.0959)	(0.0025)	(0.0651)	(0.0326)
ln Output Capacity (MWe)	-0.3375	0.0121	-2.573*	0.7419
	(2.110)	(0.0326)	(1.500)	(0.5964)
Number of Links	34.43***	0.0771***	8.227***	2.911***
	(2.339)	(0.0087)	(0.4667)	(0.2972)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,169	2,169	2,169	2,169
R^2	0.94925	0.83598	0.70416	0.76263
Within R^2	0.68136	0.15818	0.26165	0.26795

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table provides the DID estimates of how regulatory stringency affects the technological connections of regulated firms. All explanatory variables in the analysis are standardized. Part (1) of the table displays an aggregation of all types of technological connections a firm maintains, encompassing three categories: *License-To*, *License-From*, and technology collaboration partnerships.

Table A.3.10: Impact of Regulation Stringency on Technological Network (2)

Dependent Variables:	No. of License-To Links	No. of License-From Links	License-To Links (Share in Tech)	License-From Links (Share in Tech)	No. of Research Collaboration
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
$\Delta Stringency \times Year = 2013$	-0.1058***	0.0009	0.0122	-0.0013	0.8430***
	(0.0209)	(0.0010)	(0.0204)	(0.0009)	(0.1659)
$\Delta Stringency \times Year = 2014$	-0.1632***	-0.0016	0.1282***	0.0049***	0.0807
	(0.0194)	(0.0010)	(0.0185)	(0.0007)	(0.0942)
$\Delta Stringency \times Year = 2015$	-0.0838***	0.0013	0.1246***	0.0050***	-0.3431**
	(0.0176)	(0.0013)	(0.0172)	(0.0007)	(0.1716)
Verified Emissions (tCO2e)	0.0834	-0.0040	0.0932	-0.0038	0.6209
	(0.1170)	(0.0030)	(0.1034)	(0.0053)	(0.5591)
Regulated Plants (%)	0.5380**	0.0256**	-0.0071	-0.0166	-3.836
	(0.2698)	(0.0123)	(0.2050)	(0.0173)	(2.790)
Δ No. of Regulated Plants	0.1233	0.0003	0.1252	0.0031***	-0.3895
	(0.1102)	(0.0007)	(0.0834)	(0.0012)	(0.4916)
Disclosure	0.0505	-0.0033	0.0294	0.0006	-0.0746
	(0.0429)	(0.0021)	(0.0234)	(0.0020)	(0.2809)
Total Assets ($M)	2.847***	0.0229	0.3850	0.0169	-30.90***
	(0.5861)	(0.0185)	(0.2360)	(0.0138)	(8.875)
Debt to Equity	-0.0101	-0.0027*	0.0039	0.0012	0.1526
	(0.0130)	(0.0016)	(0.0077)	(0.0009)	(0.0998)
ln Output Capacity (MWe)	0.6572*	0.1672	0.3898	0.1485	-1.344
	(0.3987)	(0.1395)	(0.2796)	(0.1136)	(2.129)
Number of Links	2.680***	0.0170	0.5953***	-0.0231***	31.15***
	(0.3028)	(0.0152)	(0.1570)	(0.0057)	(2.557)
Fixed-effects					
company_std	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	2,169	1,883	2,169	1,883	2,169
R^2	0.94963	0.83102	0.98724	0.92607	0.91268
Within R^2	0.21807	0.01033	0.03759	0.04266	0.62844

Clustered (company_std) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table provides the DID estimates of how regulatory stringency affects the technological connections of regulated firms. All explanatory variables in the analysis are standardized. Part (2) of the table specifically focuses on the results for *License-To* and *License-From* links. The units presented for some variables are those before standardization.

Table A.3.10: Impact of Regulation Stringency on Technological Network (3)

Dependent Variables:	No. of License-To Regulated	License-To Regulated (Share in License-To)	No. of License-From Regulated	License-From Regulated (Share in License-From)
Model:	(1)	(2)	(3)	(4)
Variables				
$\Delta Stringency \times Year = 2013$	-0.0261**	-0.3043***	-0.0043	-0.0729
	(0.0103)	(0.0915)	(0.0066)	(0.1000)
$\Delta Stringency \times Year = 2014$	-0.0332***	-0.2634**	-0.0035	-0.0658
	(0.0083)	(0.1197)	(0.0056)	(0.1059)
$\Delta Stringency \times Year = 2015$	-0.0062	-0.0302	-0.0013	-0.0727
	(0.0038)	(0.0813)	(0.0045)	(0.0976)
Verified Emissions (tCO2e)	0.0728	0.2957**	0.0281	-0.0161
	(0.0820)	(0.1303)	(0.0321)	(0.0911)
Regulated Plants (%)	0.0552	0.0063	-0.1350	-0.0331
	(0.1499)	(0.0137)	(0.1514)	(0.0252)
Δ No. of Regulated Plants	0.0184	0.0135	0.0175	0.0082
	(0.0147)	(0.0087)	(0.0161)	(0.0089)
Disclosure	-0.0061	0.0011	0.0086	-0.0156
	(0.0058)	(0.0052)	(0.0119)	(0.0126)
Total Assets ($M)	0.3380***	-0.0173	0.0348	-0.6579***
	(0.1201)	(0.0199)	(0.0773)	(0.2188)
Debt to Equity	0.0013	-0.0050	0.0002	-0.0038
	(0.0032)	(0.0076)	(0.0015)	(0.0029)
ln Output Capacity (MWe)	-0.1070*	-0.1776*	-0.0367	-0.2094
	(0.0621)	(0.0917)	(0.0728)	(0.2788)
Number of Links	0.2858***	0.0603***	0.2408***	0.0284
	(0.0669)	(0.0133)	(0.0409)	(0.0232)
Fixed-effects				
company_std	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,169	564	2,169	566
R^2	0.86698	0.91271	0.90376	0.85753
Within R^2	0.02916	0.09660	0.03245	0.05362

Clustered (company_std) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table provides the DID estimates of how regulatory stringency affects the technological connections of regulated firms. All explanatory variables in the analysis are standardized. Part (3) of the table shows the results for *License-To* and *License-From* with firms that are also regulated. The units presented for some variables are those before standardization.

Appendix B

Appendix For Chapter 2

B.1 Appendix 2.A

Figure B.1.1: Example of the Input Page

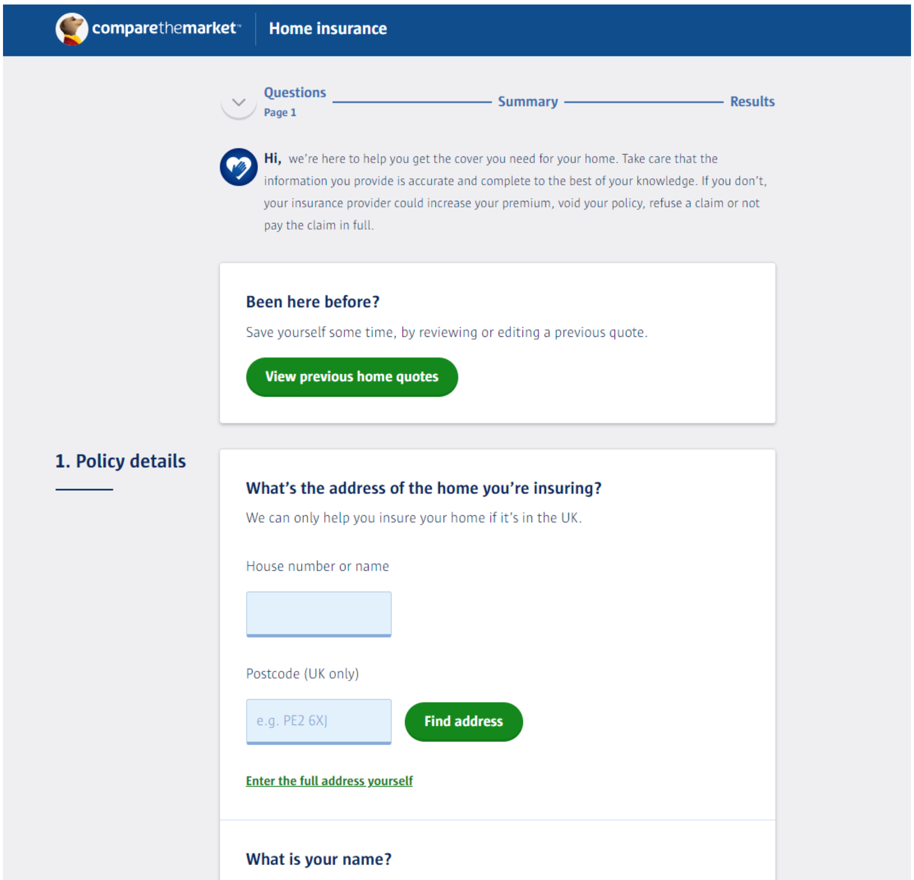


Table B.1.1: Inputs Used in Data Collection

Input Variables	Questions Asked and Descriptions
	Real Property Features
Address	What's the address of the home you're insuring? UK address including door number and post code.
Property Type	What kind of home do you want to insure? Ground floor flat, detached house, etc.
Self-Contained	Is it self-contained (no shared rooms) with its own lockable entrance? Yes for all properties.
Year Built	What year was your property built? The best estimate of the real property is entered.
Rooms	How many rooms does your property have? Real information about the number of bedrooms, living rooms, bathrooms, and other rooms is entered based on floor plan.
Wall & Roof	What are the external walls and the roof made of? How much of the roof is flat? Answers based on the best estimate of the real property.
Rebuild Cost	What would it cost to rebuild your property, excluding land value? Answers are adjusted based on the automatic estimate given by comparethemarket.com.
Surroundings	Are there any trees taller than 10 metres (33ft) within 5 metres (17ft) of your property? Is your property within 400 metres (0.25 mile) of water? Answers based on the best estimate.
	Fixed Property-Related Inputs
Cover Type	What kind of home insurance policy you need? Choose from: buildings and contents cover, buildings cover, and contents cover. *Fixed value*: buildings cover.
Start Date	When, within 30 days, would you like your cover to start? *Fixed value*: fixed days from the data collection date.
Good State	Is your property in a good state of repair? *Fixed value*: Yes.
Building Work	Is your property undergoing any building work? *Fixed value*: No.
Smoke Detector	Do you have working smoke detectors? *Fixed value*: Yes.
Business Use	Do you or anyone living in your property use it for business purposes? *Fixed value*: No.
Listed Building	Is your property a listed building? *Fixed value*: No.
History	Has your property ever been flooded? Has your property ever had cracks on its external walls? Has your property ever had any underpinning or structural support? Has your flat ever suffered from subsidence or ground movement? *Fixed value*: No.
	Varying Policy Choice Inputs
Add On	Would you like to add Accidental Damage, Home Emergency, Legal Assistance or cover for Replacement Locks & Keys for your buildings?
Voluntary Excess	If you had to make a claim, what is the maximum voluntary excess (deductible) you'd like to pay? Fixed value: £250.

Table B.1.1: Inputs Used in Data Collection

Input Variables	Questions Asked and Descriptions
	Varying Policyholder-Related Inputs
Title	Mr., Mrs., Ms., and Miss. An indicator for gender.
Names	First name and Surname. A potential indicator for race.
Birthday	Year, month and day. An indicator for age.
Marital	What is your marital status? Choices: Married, Civil partnered, Single, Common law partnered/cohabiting, Divorced/dissolved, Separated, and Widowed/surviving civil partner.
Employ	What is your employment status? Choices: Employed full-time, Employed part-time, Unemployed, Self-employed, Houseperson, Full or part-time Education, Retired, Not employed due to disability/illness.
Job Title	What is your job title? The list of occupations is provided by the Association of British Insurers (ABI).
Industry	What industry do you work in? The list of occupations is provided by the ABI.
	Varying Household-Related Inputs
Residents	Who lives in your property? Choices: Policyholder and family members, Policyholder only, Policyholder in a a shared property, Policyholder and lodgers, Policyholder and students.
People	How many people live in your property? Specify the number of adults and children, respectively.
Bankrupt	Have you or anyone living in the property ever been declared bankrupt?
Recent Claims	Have you or anyone living in the property made any home insurance claims in the last 5 years? If Yes, need to specify the reason, time, amount of claim, and in which property.
Year Lived	How many years have you lived in your property? Calculated based on property transaction date.
Ownership	Do you own or rent your home? Since buildings cover can only be bought for owned properties, the only two choices here is ”Mortgaged” or ”Owned”.
No Claims	For how many years have you continuously held buildings insurance without any claims? Choices range from the minimum of ”None” to the maximum of ”9 years or more”.
	Fixed Policyholder and Household-Related Inputs
Other Job	Do you have another job or a part-time job too? Fixed value: No.
Other Holders	Would you like to add anyone else as a policyholder? Fixed value: No.
Pets	Do you have any cats or dogs living with you? Fixed value: No.
Smokers	Does anyone living in the property smoke? Fixed value: No.
Empty	Will your property be left empty for more than 30 consecutive days? Fixed value: No.
Main Home	Is this property your main home? Fixed value: Permanent main residence.
Crime	Have you or anyone living in the property ever been convicted of, or is awaiting trial for, any crime excluding motoring offences? Fixed value: No.
Refusal	Have you or anyone living in the property had home insurance refused, cancelled, declined or void or had any conditions imposed? Fixed value: No.
Payment	How do you usually pay for your home insurance? Fixed value: One annual payment.

Figure B.1.2: Example of the Output Page

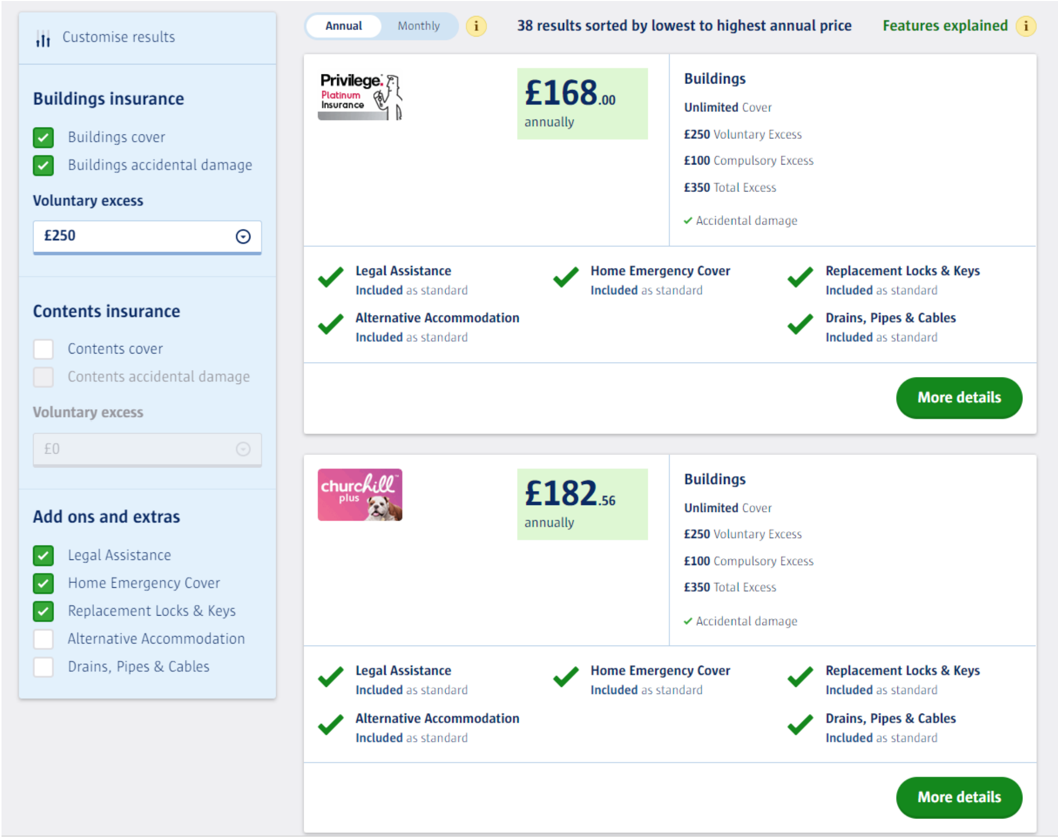
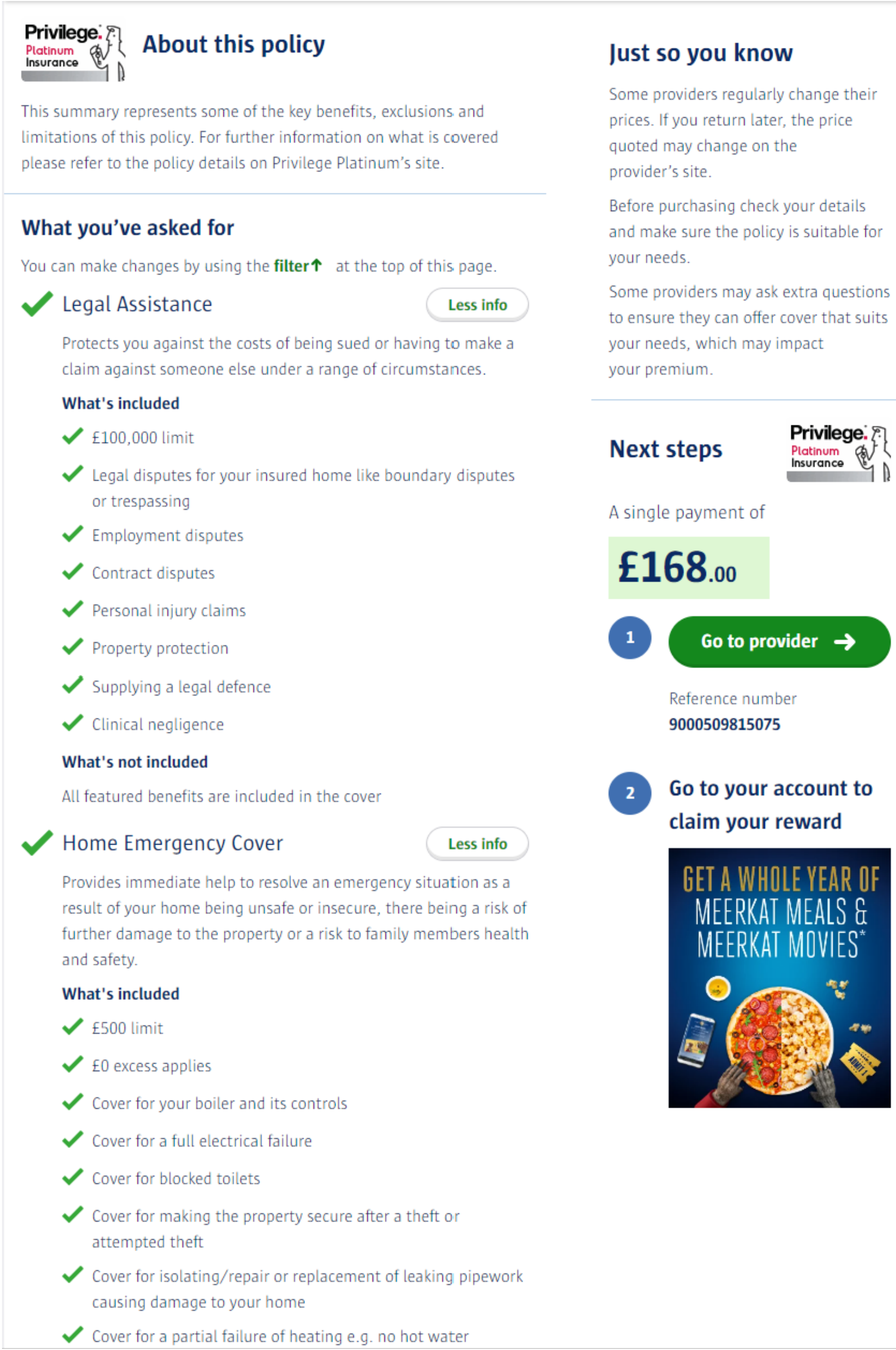


Figure B.1.3: Example of the Output Page in Detail



Privilege. Platinum Insurance

About this policy

This summary represents some of the key benefits, exclusions and limitations of this policy. For further information on what is covered please refer to the policy details on Privilege Platinum's site.

What you've asked for

You can make changes by using the **filter** at the top of this page.

Legal Assistance — Less info

Protects you against the costs of being sued or having to make a claim against someone else under a range of circumstances.

What's included

- £100,000 limit
- Legal disputes for your insured home like boundary disputes or trespassing
- Employment disputes
- Contract disputes
- Personal injury claims
- Property protection
- Supplying a legal defence
- Clinical negligence

What's not included

All featured benefits are included in the cover

Home Emergency Cover — Less info

Provides immediate help to resolve an emergency situation as a result of your home being unsafe or insecure, there being a risk of further damage to the property or a risk to family members health and safety.

What's included

- £500 limit
- £0 excess applies
- Cover for your boiler and its controls
- Cover for a full electrical failure
- Cover for blocked toilets
- Cover for making the property secure after a theft or attempted theft
- Cover for isolating/repair or replacement of leaking pipework causing damage to your home
- Cover for a partial failure of heating e.g. no hot water

Just so you know

Some providers regularly change their prices. If you return later, the price quoted may change on the provider's site.

Before purchasing check your details and make sure the policy is suitable for your needs.

Some providers may ask extra questions to ensure they can offer cover that suits your needs, which may impact your premium.

Next steps

Privilege. Platinum Insurance

A single payment of

£168.00

1 Go to provider

Reference number
9000509815075

2 Go to your account to claim your reward

B.2 Appendix 2.B

Table B.2.1: Baseline Regression Results

Dependent Variable:	Annual Price				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Total Excess	-0.4458***	-0.4628***	-0.4642***	-0.4730***	-0.0491
	(0.1162)	(0.0394)	(0.1232)	(0.1307)	(0.0995)
Accidental Damage Included	105.1***	69.98***	73.59***	53.57***	41.08***
	(22.73)	(13.22)	(17.91)	(12.13)	(9.821)
Legal Assistance Included	-13.36	9.406	12.86	37.23***	41.19***
	(20.20)	(10.56)	(11.58)	(8.681)	(9.854)
Home Emergency Included	16.15	42.52***	42.53**	39.87***	35.50***
	(22.50)	(13.70)	(18.30)	(7.033)	(9.934)
Replace Lock & Key Included	-138.5**	-34.46	-38.51	-35.42	-35.71
	(50.48)	(42.58)	(49.12)	(38.79)	(35.97)
Drains, Pipes and Cables Included	-0.0081	94.36***	90.06***	86.13***	89.84***
	(18.52)	(25.48)	(31.32)	(24.19)	(32.75)
Fixed-effects					
Date	Yes	Yes	Yes	Yes	Yes
Policy		Yes	Yes		
Property			Yes		
Policy-Property				Yes	Yes
Individual-Property					Yes
Fit statistics					
Observations	13,916	13,916	13,916	13,916	13,916
RMSE	189.35	164.33	160.64	113.12	101.10
Adjusted R^2	0.48177	0.60718	0.62381	0.79070	0.82895
Within Adjusted R^2	0.11347	0.12044	0.12671	0.21313	0.03417

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

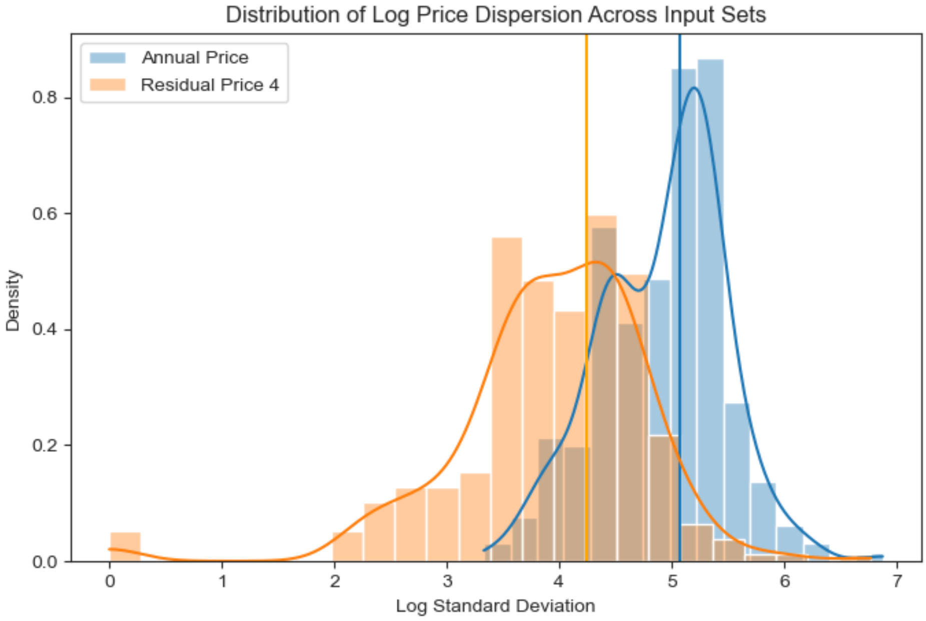


Figure B.2.1: Distribution of Price Dispersion

The figure plots the distribution of the log-scaled price dispersion across individuals. The blue line is the distribution of the log standard deviation of the raw annual prices. The orange line is the distribution of the log standard deviation of the residual prices from $Annual.Price_{ipt} = \gamma_t + \lambda_h * \alpha_p + \beta Choices_{ipt} + \epsilon_{ipt}$ (detailed in column (4) Table B.2.1). The vertical lines represent log of the average standard deviation, with the value equal to 5.074 for the blue line and 4.239 for the orange line.

Variables	Count	Mean	SD	Min	Median	Max
Group of individuals by date, property, policy and policy choices						
Observation-Level						
Residual Price	12211	29.89	74.40	0.00	13.42	5014.87
Group-Level						
Number of Individuals	2885	4.23	2.72	2.00	3.00	20.00
Average Annual Price	2885	409.09	244.52	69.07	339.85	2378.61
SD of Annual Price	2885	32.50	70.50	0.00	17.50	2803.78
CV of Annual Price	2885	0.08	0.09	0.00	0.05	1.40
Range of Annual Price	2885	71.63	168.44	0.00	33.94	6313.15

B.3 Appendix 2.C

Table B.3.1: Pricing With Known Customer Preferences

<table>
<tr><th colspan="2"></th><th>Provider A</th><th>Provider B</th></tr>
<tr><td rowspan="3">If $c_A < c_B$</td><td>Type 1</td><td>$p_{1A} = c_B + \nu_A - \delta$</td><td>$p_{1B} = c_B$</td></tr>
<tr><td>Type 2</td><td>$p_{2A} = c_B - \delta$</td><td>$p_{2B} = c_B$</td></tr>
<tr><td colspan="3">Both types buy from A and get $U_i = \overline{\nu} - c_B + \delta$</td></tr>
<tr><td rowspan="3">If $c_B + \nu_A < c_A$</td><td>Type 1</td><td>$p_{1A} = c_A$</td><td>$p_{1B} = c_A - \nu_A - \delta$</td></tr>
<tr><td>Type 2</td><td>$p_{2A} = c_A$</td><td>$p_{2B} = c_A - \delta$</td></tr>
<tr><td colspan="3">Both types buy from B and get $U_1 = \overline{\nu} + \nu_A - c_A + \delta$
and $U_2 = \overline{\nu} - c_A + \delta$, respectively.</td></tr>
<tr><td rowspan="2">If $c_B + \nu_A = c_A$</td><td>Type 1</td><td>$p_{1A} = c_A$</td><td>$p_{1B} = c_A - \nu_A$</td></tr>
<tr><td colspan="3">Type 1 randomly choose between provider A and B
and get $U_1 = \overline{\nu} + \nu_A - c_A$</td></tr>
<tr><td rowspan="3">If $c_B < c_A < c_B + \nu_A$</td><td>Type 1</td><td>$p_{1A} = c_B + \nu_A - \delta$</td><td>$p_{1B} = c_B$</td></tr>
<tr><td>Type 2</td><td>$p_{2A} = c_A$</td><td>$p_{2B} = c_A - \delta$</td></tr>
<tr><td colspan="3">Type 1 buy from A and get $U_1 = \overline{\nu} - c_B + \delta$
Type 2 buy from B and get $U_2 = \overline{\nu} - c_A + \delta$</td></tr>
<tr><td rowspan="2">If $c_B = c_A$</td><td>Type 2</td><td>$p_{2A} = c_A$</td><td>$p_{2B} = c_B$</td></tr>
<tr><td colspan="3">Type 2 randomly choose between provider A and B
and get $U_2 = \overline{\nu} - c_A = \overline{\nu} - c_B$</td></tr>
</table>

Table B.3.2: Annual Price by Individual and Provider Characteristics - Breakdown

Dependent Variable:	Annual Price		
Model:	(1)	(2)	(3)
Variables			
Non-Insurance Focus	92.46	32.53	66.24**
	(66.68)	(56.13)	(29.38)
Non-Insurance Focus × Name Implied Race = Arab	-176.4**		
	(62.47)		
Non-Insurance Focus × Name Implied Race = Asian	119.5		
	(71.56)		
Non-Insurance Focus × Marital Status = Divorced		-18.32	
		(17.58)	
Non-Insurance Focus × Marital Status = Single		-7.032	
		(94.22)	
Non-Insurance Focus × Employment Status = Houseperson			-26.56
			(41.38)
Non-Insurance Focus × Employment Status = Not Employed			102.5
			(68.02)
Non-Insurance Focus × Employment Status = Part-time			10.94
			(34.71)
Non-Insurance Focus × Employment Status = Retired			-58.31
			(43.61)
Non-Insurance Focus × Employment Status = Self-employed			-17.33
			(30.66)
Non-Insurance Focus × Employment Status = Unemployed			115.2**
			(51.66)
Name Implied Race = Arab	49.00**		
	(17.10)		
Name Implied Race = Asian	-28.52		
	(20.54)		
Marital Status = Divorced		18.98	
		(10.97)	
Marital Status = Single		-3.508	
		(14.98)	
Employment Status = Houseperson			0.6337
			(13.00)
Employment Status = Not employed			8.005
			(12.35)
Employment Status = Part-time			-15.44
			(12.39)
Employment Status = Retired			18.04
			(14.59)
Employment Status = Self-employed			1.972
			(8.421)
Employment Status = Unemployed			35.61
			(24.76)
Fixed-effects			
Matched Group	Yes	Yes	Yes
Fit statistics			
Observations	92	192	963
R^2	0.22232	0.41332	0.68023
Within R^2	0.14135	0.27823	0.15234

Clustered (group_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix C

Appendix For Chapter 3

C.1 Appendix 3.A

Table C.1.1: Corporate Green Bond Issuance by BNEF Rating

BNEF Rating	Number of Issuers	Number of Bonds	With External Reviews	Amount Issued ($Billion)
A1 Main Driver	83	307	110	42.534
A2 Considerable	17	32	24	7.326
A3 Moderate	41	110	91	42.481
A4 Minor	333	1038	806	328.175
No Rating	605	1513	1190	295.443
Total*	1079	3000	2221	715.959

**As of May 26th, 2021*

The Bloomberg New Energy Finance (BNEF) 'clean energy exposure' rating is an estimate of the percent of an organisation's value that is attributable to its activities in renewable energy, energy smart technologies, carbon capture and storage (CCS) and carbon markets. *A1 Main Driver* are those with 50 to 100% of their revenues (along with other available metrics such as EBITDA) derived from clean energy related activities. *A2 Considerable* is for those with 25 to 49% of their revenues derived from such activities. *A3 Moderate* and *A4 Minor* have 10 to 24% and less than 10% of their revenues derived from such activities, respectively. The rating is at the firm-level not at the security-level, so the table above might count a firm multiple times in a year if that firm has issued multiple bonds that year.

Table C.1.2: Corporate Green Bond Issuance by Sub-Sector

Sector (BICS2*)	Number of Issuers	Number of Bonds	With External Reviews	Amount Issued ($Billion)
Banks	207	731	619	194.646
Real Estate	204	600	486	94.153
Power Generation	125	335	233	78.628
Renewable Energy	59	294	103	20.835
Utilities	110	271	189	112.910
Consumer Finance	22	110	99	25.972
Industrial Other	41	90	67	13.477
Travel & Lodging	18	64	37	14.051
Financial Services	35	63	43	7.341
Diversified Banks	18	56	42	31.271
Transportation & Logistics	25	50	41	21.677
Commercial Finance	24	41	30	7.757
Automobiles Manufacturing	12	31	16	13.245
Waste & Environment Services & Equipment	19	29	25	5.967
Forest & Paper Products Manufacturing	10	28	25	6.563
Refining & Marketing	7	17	15	2.600
Chemicals	11	15	13	4.444
Life Insurance	11	15	13	7.334
Metals & Mining	9	15	9	2.950
Food & Beverage	12	13	11	3.703
Semiconductors	7	11	10	4.495
Hardware	4	10	9	2.467
Containers & Packaging	6	9	7	5.173
Electrical Equipment Manufacturing	8	9	5	1.770
Consumer Products	5	7	5	0.808
Auto Parts Manufacturing	5	6	2	2.159
Machinery Manufacturing	5	6	6	1.531
Supermarkets & Pharmacies	3	6	5	0.859
Wireline Telecommunications Services	6	6	6	3.538
Home Improvement	3	5	4	0.925
Homebuilders	5	5	4	0.498
Wireless Telecommunications Services	3	5	5	3.468
Communications Equipment	1	4	4	4.720
Health Care Facilities & Services	2	4	2	0.518
Railroad	2	4	3	1.591
Funds & Trusts	3	3	3	0.780
Integrated Oils	3	3	1	0.324
Property & Casualty Insurance	3	3	3	2.930
Retail - Consumer Discretionary	3	3	2	0.747
Apparel & Textile Products	2	2	2	0.646
Cable & Satellite	2	2	2	1.112
Construction Materials Manufacturing	2	2	2	0.496
Consumer Services	2	2	1	0.145
Educational Services	2	2	1	0.585
Entertainment Resources	2	2	1	0.142
Manufactured Goods	2	2	2	0.495
Software & Services	2	2	2	0.120
Airlines	1	1	1	0.089
Coal Operations	1	1	1	0.436
Department Stores	1	1	1	0.089
Internet Media	1	1	0	0.800
Managed Care	1	1	1	0.575
Medical Equipment & Devices Manufacturing	1	1	1	0.837
Retail - Consumer Staples	1	1	1	0.569
Total*	1079	3000	2221	715.959

**Bloomberg Industry Classification Systems Level 2*

***As of May 25th, 2021*

Table C.1.3: Green Bond Issuer by Year and BNEF Rating

Year	A1 Main Driver	A2 Considerable	A3 Moderate	A4 Minor	No Rating	Total
2013	1	1	0	3	1	6
2014	8	3	2	12	9	34
2015	11	1	3	20	12	47
2016	12	0	3	33	37	85
2017	16	3	11	49	85	164
2018	15	2	7	73	128	225
2019	20	5	19	113	202	359
2020	23	3	10	135	209	380
2021*	19	6	16	88	172	301
Total*	125	24	71	526	855	1601

**As of May 26th, 2021*

Table C.1.4: Corporate Green Bond Issuance by Region

Region	Number of Bonds	With External Reviews	Amount Issued ($Billion)
Eastern Asia	786	582	203.297
Western Europe	702	587	178.173
Northern Europe	629	562	94.323
Northern America	350	110	109.309
South-Eastern Asia	189	146	9.325
Southern Europe	133	108	68.780
Latin America & Caribbean	85	26	18.053
Southern Asia	40	28	11.993
Australia and New Zealand	32	29	9.169
Eastern Europe	25	20	7.735
Middle East & Africa	20	17	4.896
Other Asia	9	6	0.906
Total*	3000	2221	715.959

**As of May 26th, 2021*

Table C.1.5: Corporate Green Bond Issuance by Currency

Currency	Number of Bonds	With External Reviews	Amount Issued ($Billion)
EUR	757	643	311.868
USD	582	278	185.191
SEK	379	343	31.465
CNY	373	276	111.070
JPY	170	143	14.245
MYR	134	101	1.244
NOK	89	83	7.207
BRL	70	22	2.254
TWD	52	41	4.282
GBP	49	40	12.072
KRW	47	21	3.944
HKD	36	18	3.181
CAD	35	27	9.466
INR	34	25	1.381
AUD	30	23	4.534
CHF	30	29	5.870
THB	26	20	1.714
TRY	25	22	0.358
ZAR	13	13	0.184
NZD	12	12	0.938
MXN	11	5	0.694
IDR	8	7	0.043
PLN	7	5	0.516
DKK	6	5	0.000
SGD	5	5	0.950
HUF	4	2	0.406
PHP	3	2	0.365
CZK	2	2	0.060
KES	2	2	0.065
NGN	2	1	0.065
RON	2	1	0.114
RUB	2	2	0.113
COP	1	1	0.066
NAD	1	0	0.005
PEN	1	1	0.030
Total*	3000	2221	715.959

**As of May 26th, 2021*

C.2 Appendix 3.B

Table C.2.6: List of Output Variables

ESG Variables	Descriptions
ESG Score	- An overall company score based on the self-reported information in the environmental, social and corporate governance pillars.
Environmental Pillar Score	- Measures a company's impact on living and non-living natural systems, including the air, land and water, as well as complete ecosystems.
Environmental Products	-Does the company report on at least one product line or service that is designed to have positive effects on the environment or which is environmentally labeled and marketed?
Eco-Design Products	- Does the company report on specific products which are designed for reuse, recycling or the reduction of environmental impacts?
Renewable Energy Products	- Does the company develop products or technologies for use in the clean, renewable energy (such as wind, solar, hydro and geo-thermal and biomass power)?
Sustainable Building Products	- Does the company develop products and services that improve the energy efficiency of buildings?
Scope 1 and 2 CO2 (MT)	- Direct (scope1) + Indirect (scope 2) carbon dioxide (CO2) and CO2 equivalents emission in million tonnes Maximum payment of a policy when a claim is made
Scope 1 and 2 to Rev (T/M$)	Total CO2 and CO2 equivalents emission in tonnes divided by net sales or revenue in US dollars in million.
All Scope CO2 (MT)	Total (Scope 1-3) CO2 equivalent emission in million tonnes.
All Scope to Rev (T/M$)	Total (Scope 1-3) CO2 equivalent emission in tonnes divided by net sales or revenue US dollars in million.
Environmental R&D Exp (M$)	Total amount of environmental R&D costs (without clean up and remediation costs).
Percentage of Green Products	Percentage of green products or services as reported by the company. green bonds, green loans, responsible environmental investing can be considered for financial sector.
Environmental Controversies	Number of controversies related to the environmental impact of the company's operations on natural resources or local communities since the last fiscal year company update.
Environmental Asset Under Mgt	Does the company report on assets under management which employ environmental screening criteria or environmental factors in the investment selection process? (relevant to asset management companies)
Environmental Project Financing	Does the company claim to evaluate projects on the basis of environmental or biodiversity risks as well? (relevant to the financial sector and focus is on project financing data)
Fossil Fuel Divestment Policy	Does the financial company have a public commitment to divest from fossil fuel?

C.3 Appendix 3.C

Table C.3.7: SA Index and Green Bond Issuance

	Dependent Variable: SA Index	
	(1)	(2)
Green Bond Issuer	-2.054^{***}	
	(0.184)	
Green Bond Issuer (Cast-Parent Level)		-2.084^{***}
		(0.176)
F Statistic	124.91^{***}	140.34^{***}
Degree of Freedom (df1; df2)	(1; 2253)	(1; 2253)
Observations	27,202	27,202
R^2	0.025	0.028
Adjusted R^2	0.024	0.027
Note:		*p<0.1; **p<0.05; ***p<0.01

Table C.3.8: Environmental Pillar Score and Green Bond Issuance

	Dependent Variable: Environmental Pillar Score			
	(1)	(2)	(3)	(4)
GB Issuer	24.568^{***}			
	(1.549)			
Issued the First GB		1.362	1.529	0.527
		(1.321)	(1.792)	(5.999)
GB Issue Year			-0.287	
			(1.354)	
SA Index				-4.129^{***}
				(0.846)
Issued the First GB * SA Index				-0.206
				(1.953)
F Statistic	251.49^{***}	1.0635	0.55735	7.9987^{***}
Degree of Freedom (df1; df2)	(1; 8,560)	(1; 8,560)	(2; 8,560)	(3; 2,230)
Number of Firm-Years	128,414	128,414	128,414	27,202
Number of Firms	8,561	8,561	8,561	2,254
Observations	60,422	60,422	60,422	15,344
R^2	0.034	0.0001	0.0001	0.010
Adjusted R^2	0.033	-0.165	-0.165	-0.160
Note:				*p<0.1; **p<0.05; ***p<0.01

C.4 Appendix 3.D

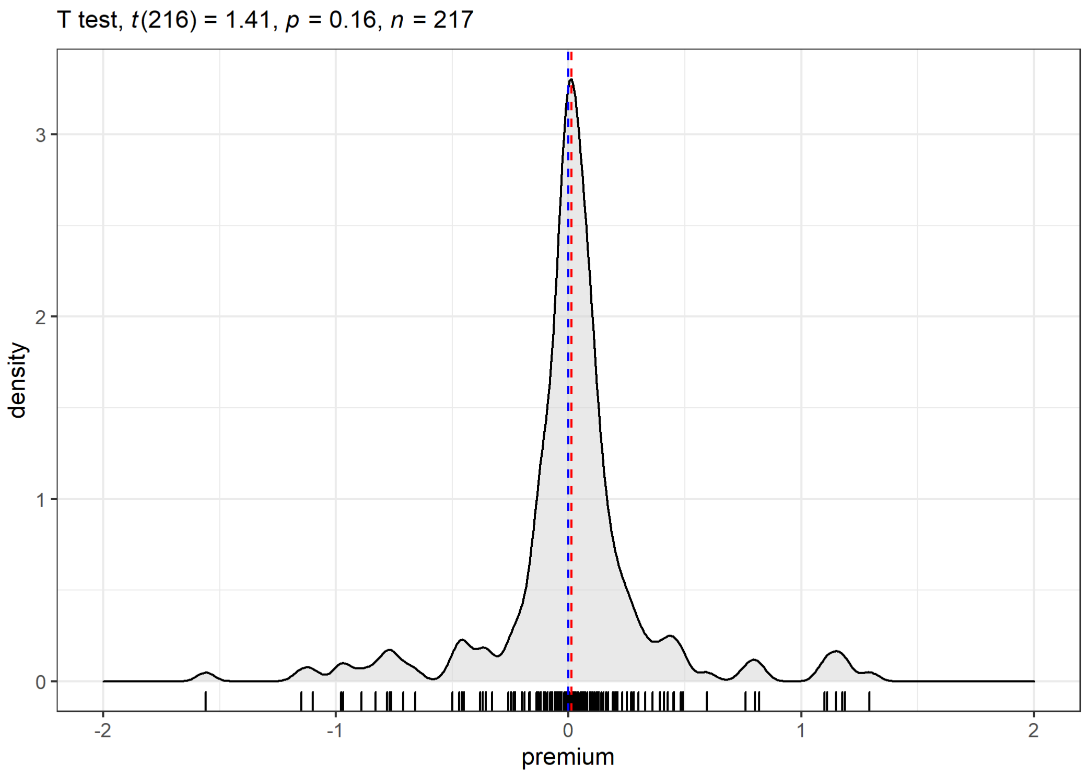


Figure C.4.1: T-Test Result for Pricing Premium (Within Three Quarters)

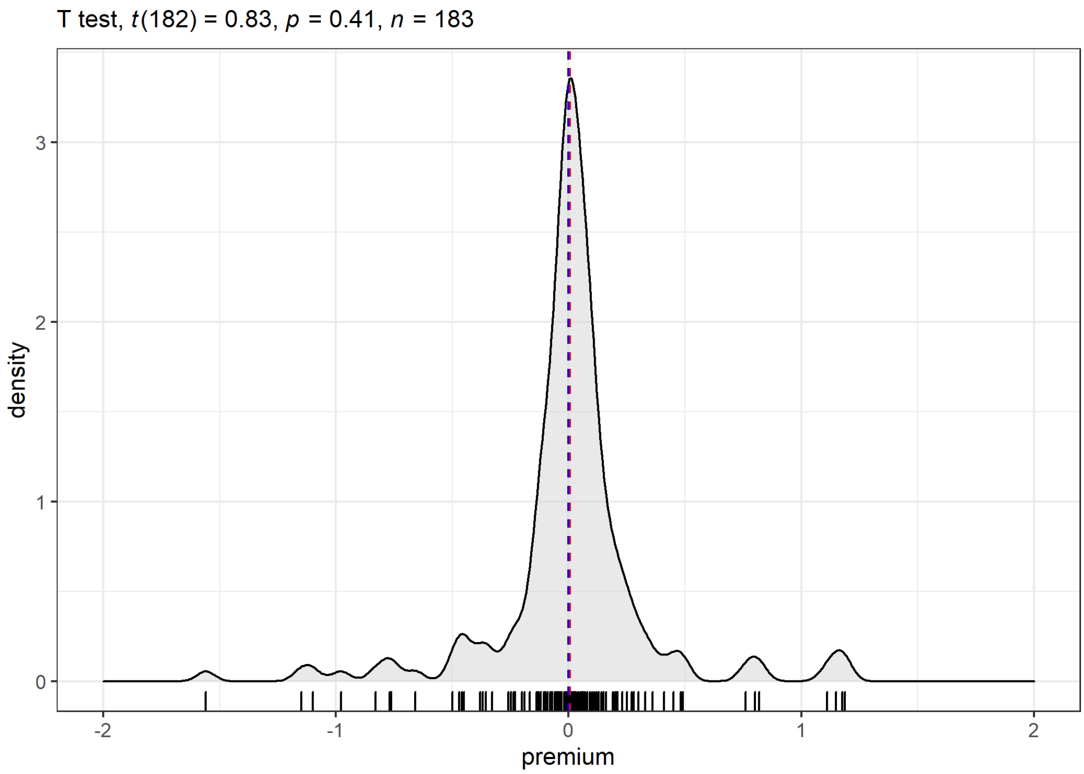


Figure C.4.2: T-Test Result for Pricing Premium (Within Two Quarters)

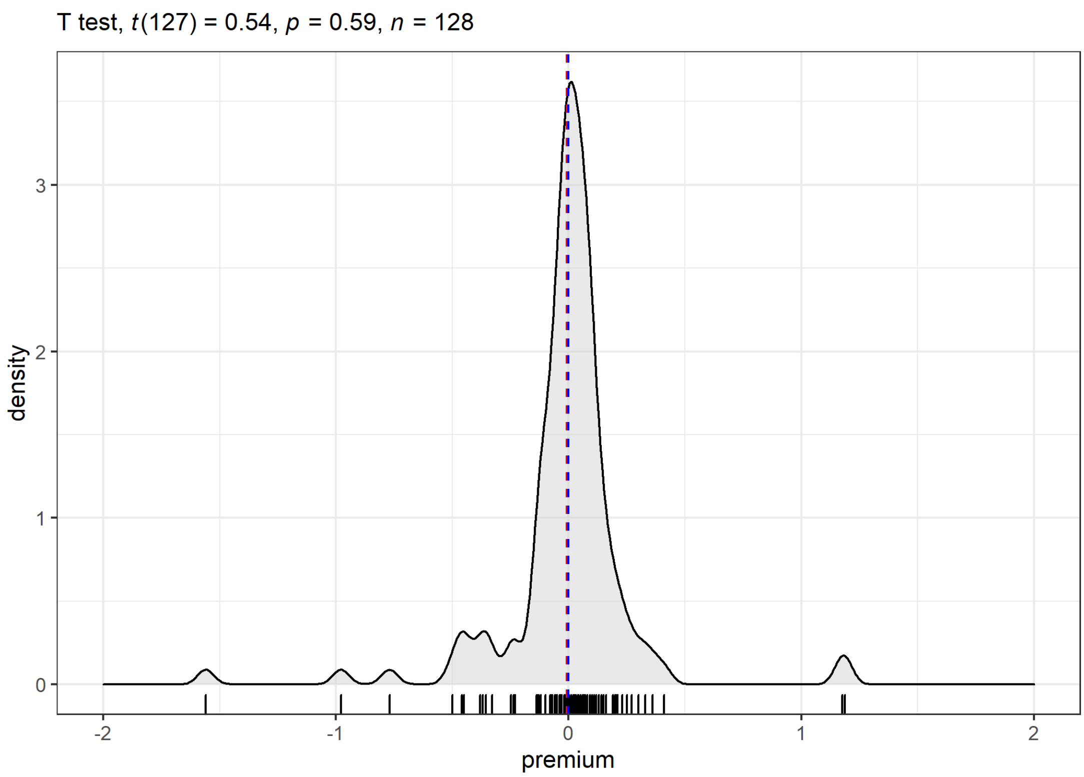


Figure C.4.3: T-Test Result for Pricing Premium (Within One Quarter)

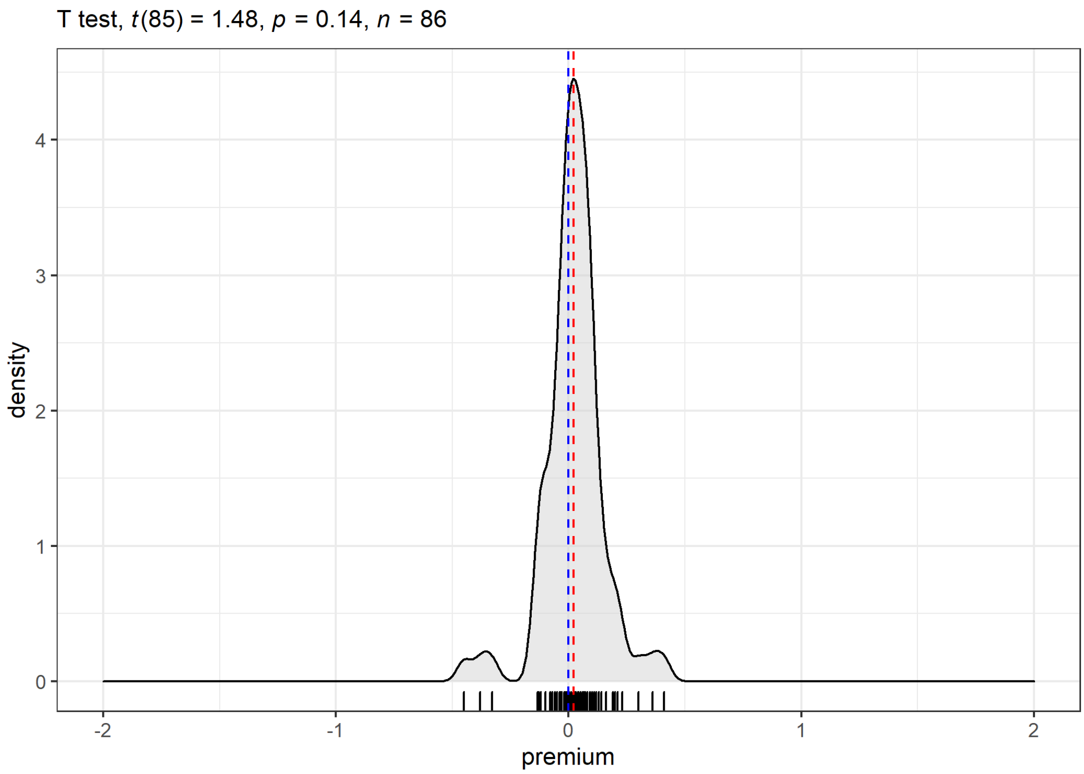


Figure C.4.4: T-Test Result for Pricing Premium (Within One Month)

Table C.4.9: Pricing Premium by Sector (Within 2Qs)

BICS2	Count	Mean	Std.Err	T.Value	P.Value
Automobiles Manufacturing	11	0.102	0.110	0.935	0.372
Banks	77	0.027	0.064	0.428	0.670
Chemicals	1	0.100			
Coal Operations	1	-0.830			
Commercial Finance	10	0.139	0.115	1.217	0.254
Consumer Finance	8	-0.119	0.032	-3.704	0.008
Diversified Banks	1	-0.979			
Financial Services	1	0.130			
Food & Beverage	2	0.015	0.055	0.273	0.830
Hardware	1	0.010			
Homebuilders	1	0.210			
Industrial Other	4	0.080	0.084	0.955	0.410
Metals & Mining	1	0.490			
Power Generation	15	0.094	0.060	1.576	0.137
Railroad	1	0.058			
Real Estate	16	-0.015	0.060	-0.258	0.800
Refining & Marketing	2	-0.214	0.046	-4.591	0.137
Renewable Energy	6	-0.155	0.095	-1.635	0.163
Transportation & Logistics	2	0.282	0.201	1.397	0.396
Travel & Lodging	6	0.074	0.033	2.256	0.074
Utilities	15	0.036	0.033	1.118	0.283
Waste & Environment Services & Equipment	1	0.090			

Table C.4.10: Pricing Premium by Issue Year (Within 2Qs)

Issue Year	Count	Mean	Std.Err	T.Value	P.Value
2013	2	-0.255	0.405	-0.630	0.642
2014	3	0.087	0.041	2.116	0.169
2015	5	-0.091	0.435	-0.209	0.845
2016	7	0.011	0.045	0.241	0.818
2017	16	-0.112	0.122	-0.913	0.376
2018	21	0.036	0.094	0.385	0.704
2019	31	-0.017	0.045	-0.370	0.714
2020	45	0.107	0.090	1.182	0.244
2021	53	0.039	0.023	1.708	0.094

Table C.4.11: Pricing Premium by Issuing Currency (Within 2Qs)

Currency	Count	Mean	Std.Err	T.Value	P.Value
AUD	2	0.151	0.052	2.942	0.209
BRL	5	0.052	0.232	0.224	0.833
CHF	1	0.058			
CNY	52	0.004	0.054	0.071	0.943
EUR	35	0.116	0.099	1.170	0.250
HKD	10	-0.034	0.074	-0.462	0.655
IDR	2	0.575	0.575	1.000	0.500
INR	9	-0.292	0.185	-1.582	0.152
JPY	19	0.056	0.025	2.280	0.035
KRW	19	-0.022	0.037	-0.605	0.553
MXN	1	0.150			
NOK	1	0.100			
SEK	2	-0.024	0.084	-0.281	0.825
TRY	3	-0.153	0.258	-0.595	0.612
TWD	13	0.025	0.027	0.908	0.382
USD	8	0.063	0.277	0.226	0.828
ZAR	1	0.410			

Table C.4.12: Pricing Premium by Issuer BNEF Rating (Within 2Qs)

BNEF Rating	Count	Mean	Std.Err	T.Value	P.Value
A1 Main Driver	7	-0.036	0.070	-0.512	0.627
A2 Considerable	1	0.060			
A3 Moderate	5	-0.124	0.097	-1.272	0.272
A4 Minor	103	0.033	0.049	0.676	0.501
No Rating	67	0.031	0.037	0.839	0.405