# The Green Bonds Premium Puzzle

*Evidence from Causal Machine Learning*

MASTER'S THESIS

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## Abstract

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This paper measures the greenium effect by using a novel tool from the causal machine learning literature. By employing the causal forest algorithm, we aim to estimate the average treatment effect (ATE) as well as the conditional average treatment effect (CATE) of a bond labelled as green in the primary market. Our data universe comes from the Eikon Refinitiv database, from which we have derived three distinct data samples. We employ three different estimation strategies, including an ensemble method with propensity score matching, resulting in a total of 11 models. Overall, our results show that the greenium effect ranges from 18.6 to 103.2 basis points, with a central tendency of 43 basis points. This effect is statistically and economically significant. We further show that violating the i.i.d assumption has a small negative effect on the estimation accuracy of the average treatment effect of causal forests.

**JEL Classification** A13; G12; Q01; Q51; Q56.

**Keywords:** Sustainable Finance; Green Bonds; Greenium; Primary Market; Causal Inference; Causal Machine Learning; Causal Forest.

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# Nomenclature

**AIPW** Augmented Inverse Probability Weighting

**ATE** Average Treatment Effect

**ATT** Average Treatment Effect on the Treated

**CATE** Conditional Average Treatment Effect

**CBI** Climate Bonds Initiative

**CEM** Coarsened Exact Matching

**CF** Causal Forest

**CIA** Conditional Independence Assumption

**DGP** Data Generating Process

**GBP** Green Bond Principles

**HTE** Heterogeneous Treatment Effect

**i.i.d** identically and independently distributed

**OLS** Ordinary Least Squares

**PSM** Propensity Score Matching

**SEK** Swedish Krona

**SUTVA** Stable Unit Treatment Value Assumption

# Chapter 1

## Introduction

We only have one earth, that is certain. That we also need to treat it well in order to cope with the climate crisis surrounding the human-made rise in temperature, is also certain. Such statements have also gained prominence in the financial world in recent years. Indeed, the large financial players hold a key role in ensuring whether sustainable technologies and projects receive long-term financing or whether industries that are detrimental to the climate are cut off. Shareholders and bank customers play a pivotal role in this development by shaping demand and, in the words of Fama & French [2007], creating a "taste" for sustainability. Consequently, progress is also being made on the supply side, with a variety of so-called green products already on the market. In this context, this paper examines a particular type of debt security, namely the "green version" of a bond. These so-called green bonds differ from their conventional version in only one aspect, which is that their proceeds are earmarked for a green purpose.

Since 2016, academics have increasingly questioned the extent to which these green bonds are profitable for issuers and investors. It is argued that green bonds fetch a so-called greenium. This effect means that investors are willing to pay a premium for the green bonds, which, ceteris paribus, lowers the interest rate, due to the negative relationship between the price and the interest rate of a bond. In a nutshell, the investor bears more compared to conventional bonds, while the issuer can finance his project more cost-effectively due to a lower interest rate. Scholars have addressed this issue, but the evidence remains inconclusive. The goal of this paper is therefore to shed new light on this green bond premium puzzle. We contribute to this literature by studying the greenium in the primary market using a novel tool from the causal machine learning literature. In particular, we apply the causal forest methodology developed in Wager & Athey [2018]. By leveraging the causal inference framework from Rubin [1974], we interpret the green labeling of bonds as treatment and define our study design as selection-on-observables. In addition to gauging the average treatment effect (ATE), which we interpret as the greenium effect, causal forests are specialized in detecting heterogeneous treatment effects (HTE). Therefore, the present study also aims to analyze the possible determinants affecting the presence or absence of the greenium effect.

To answer the questions, this paper is structured as follows. Firstly, the reader is introduced thematically by outlining the underlying principles of the green bond market and the greenium. This is followed by a review of the academic literature examining the greenium in the primary market. In a second step, the data set and the methods applied are described in more depth. The description of the methodology is followed by the central part of the paper, the quantitative analysis. Therein, we verify the model assumptions, present the descriptive statistics as well as the results of the causal forest and the findings of our Monte-Carlo simulation. In Chapter 5, we reflect on the results and discuss possible limitations. We also provide an outlook on possible future research directions. Finally, we conclude this thesis in Chapter 6 with a summary of the main conclusions.

CHAPTER 2

# THEORETICAL BACKGROUND

## 2.1 Green Bond Market

Financial markets play a critical role in the transition to a low-carbon economy by mobilizing and allocating investments in green projects [OECD, 2021, p. 3]. One way to increase these investments is to develop and deploy a new set of financial instruments. The first institutions to express a desire and interest in sustainable investments were Scandinavian pension funds. The International Bank for Reconstruction and Development (IBRD), managed by the World Bank, seized on this desire and partnered with these institutional investors in 2008 to develop and deploy a new type of debt financing instrument - the green bond [WORLD BANK, 2015, p. 24]. Unlike conventional bonds, green bonds are issued to raise capital specifically to support environmental or climate projects [p. 23]. For this purpose, the first green bond was issued in November 2008 for an amount of approximately USD 440 million (SEK 3.35 billion). This simple fixed-income product helped the World Bank to further raise awareness of climate change in the financial community and provide investors with an investment vehicle to take action [p. 24]. With the rapid growth of the market, the following unanswered questions emerged: Which bond-financed projects qualify for a green label? Who is responsible for the due diligence requirements and process? As a result, market participants needed a framework to clarify the vague definitions and processes pertaining to green bonds, reducing asymmetric information between issuers and investors. The procedure for a green flag can therefore also be seen as another textbook example of AKERLOF [1970]'s market of lemons. In early 2014, a group of banks initiated the development of the Green Bond Principles (GBP), based on the practice and experience of pioneers among multilateral development banks. The GBP act as voluntary guidelines to the issuance of green bonds and are intended to promote transparency, disclosure and integrity in the development of the green bond market [p. 30]:

*"The GBP suggests a process for designating, disclosing, managing, and reporting on the proceeds of the bond. They are designed to provide issueres with guidance on the key components involved in launcing a green bond, including providing information to aids investors in evaluating the environmental impact of their green bond investments [*WORLD BANK*, 2015, p. 30]."*

Therefore, an important part of the framework is to address the potential information asymmetries between issuers and investors. Accordingly, in addition to issuer disclosures addressed by the framework, market participants rely on the second opinions and comments from academics, investment advisors, auditors, technical experts, media, and non-governmental organizations (NGOs) such as CICERO, the Climate Bonds Initiative, Det Norske Veritas (DNV), Norway, Oekom, Sustainalytics, and Vigeo, among others, to ensure increased transparency [WORLD BANK, 2015, p. 31]. The GBP defines the term "green bond," as follows [ICMA, 2022, p. 3]:

*"Green bonds are any type of bond instrument where the proceeds or an equivalent amount will be exclusively applied to finance or re-finance, in part or in full, new and/or existing eligible green projects and which are aligned with the four core components of the GBP."*

These four core components are the following [p. 4]:

1. *Use of Proceeds*;
2. *Process for Project Evaluation and Selection*;
3. *Management of Proceeds*;
4. *Reporting*.

According to the GBP, a (non-exhaustive) list of categories recognized as potentially eligible projects are the following [pp. 4–5]:

1. *Renewable* energy (including production, transmission, applicances and products);
2. *Energy efficiency* (such as in new and refurbished buildings, energy storage, district heating, smart grids, appliances and products);
3. *Pollution prevention and control* (including reduction of air emissions, greenhouse gas control, soil remediation, waste prevention, waste reduction, waste recycling and energy/ emission-efficient waste to energy);
4. *Environmentally sustainable management of living natural resources and land use* (including environmentally sustainable agriculture; environmentally sustainable animal husbandry; climate smart farm inputs such as biological crop protection or drip-irrigation; environmentally sustainable fishery and aquaculture; environmentally sustainable forestry, including afforestation or reforestation, and preservation or restoration of natural landscapes);

5. *Terrestrial and aquatic biodiversity conservation* (including the protection of coastal, marine and watershed environments);

6. *Clean transportation* (such as electric, hybrid, public, rail, non-motorised, multi-modal transportation, infrastructure for clean energy vehicles and reduction of harmful emissions);

7. *Sustainable water and wastewater management* (including sustainable infrastructure for clean and/or drinking water, wastewater treatment, sustainable urban drainage systems and river training and other forms of flooding mitigation);

8. *Climate change adaptation* (including efforts to make infrastructure more resilient to impacts of climate change, as well as information support systems, such as climate observation and early warning systems);

9. *Circular economy adapted products, production technologies and processes* (such as the design and introduction of reusable, recyclable and refurbished materials, components and products; circular tools and services); and/or certified eco-efficient products;

10. *Green buildings* that meet regional, national or internationally recognised standards or certifications for environmental performance.

With these theoretical considerations about green bonds in mind, we can now move on to some key statistics and figures that illustrate the evolution and characteristics of the green bond market. First, Figure 2.1 illustrates the development of the amounts issued by currency or bundled currency area per year according to the Eikon Refinitiv green bond universe database. The first observation that can be made is that the green bond market grows exponentially every two years until 2021, when the amount issued reaches a record USD 600 billion. Next, the largest two markets by currency are Euro and U.S. Dollar. In addition, the Chinese yuan quickly gained a place in the top 3 after Shanghai Pudong Development Bank issued its first green bond in 2016 [WANG ET AL., 2020, p. 1].

Second, Figure 2.2 visualizes the same histogram but clustered by the type of issuer. We categorized the issuers in four broad categories:

1. *Agency*: Bonds issuer by U.S. government agencies including publicly owned U.S. government-sponsored enterprises (GSEs);

2. *Corporate*: Bonds issued by firms;

3. *Govt/Treasuy/Central Bank*: Bonds issued by the Government, Treasury or Central Bank;

4. *Other Gov/Supra*: Bonds issued by Supranational Entities.

It can be observed that corporations are the largest issuer of green bonds, followed by the public sector, which is not consistent with the overall global debt security market, where the public and private sectors are more balanced. In addition, the amount outstanding in the overall global debt security market is over \$120 trillion in 2022. Thus, the proportion of the green bond market is relatively small at $\approx 0.25\%$.[1]

Finally, Figure 2.3 visualizes a global heat-map of the amount of green bonds issued in each country. The U.S. ranks first, followed by European countries and China. It is also noticeable that almost no African country, Eastern European country or Western Asian country has issued a green bond yet.

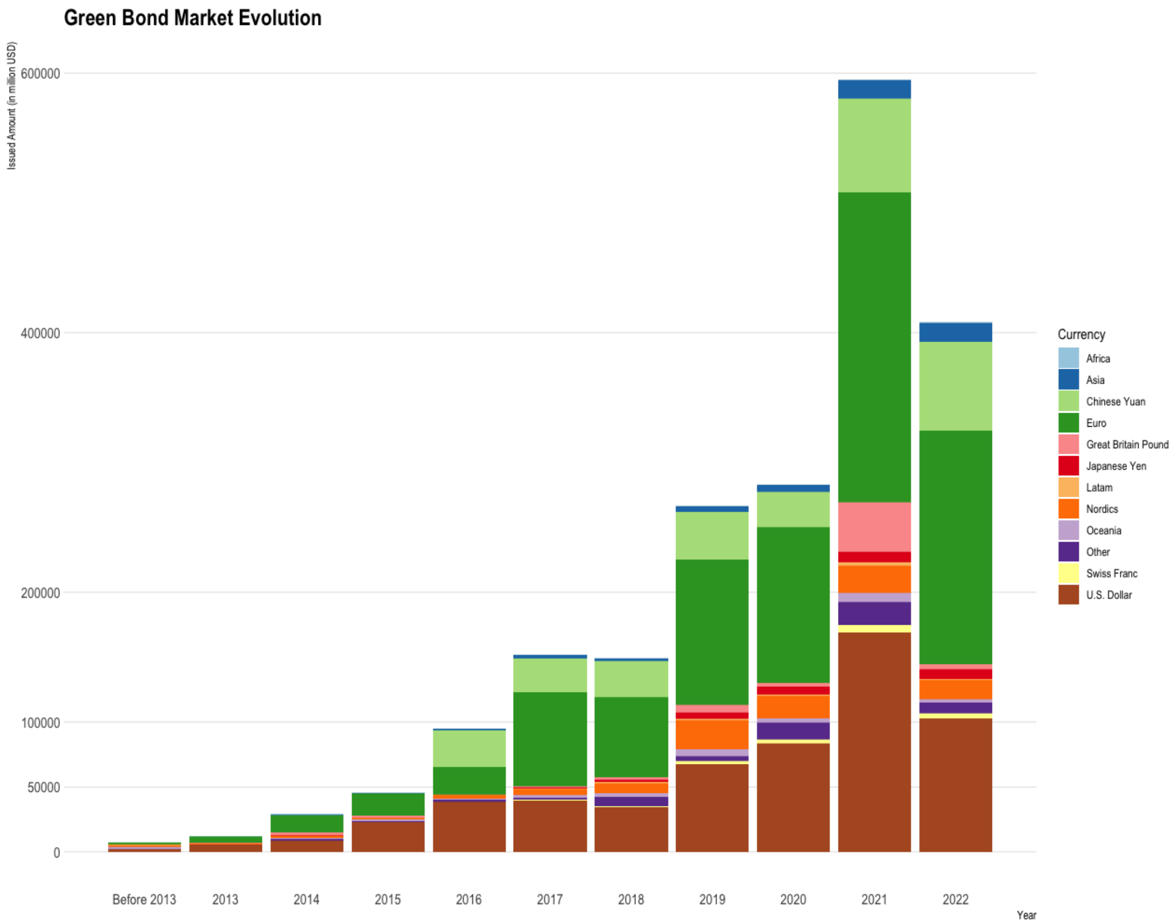



Figure 2.1: Green Bond Market Evolution by Currency / Currency Basket (own illustration).

**Source**: Eikon Refinitiv Green Bond Universe. **Green Bond types included**: Self-labeled, CBI certified, CBI aligned. **Africa**: Moroccan Dirham, Namibian Dollar, Nigerian Naira, South African Rand. **Asia**: Bangladeshi Taka, Hong Kong Dollar, Indian Rupee, Indonesian Rupiah, Macanese Pataca, Malaysian Ringgit, Philippine Peso, Singapore Dollar, Sri Lankan Rupee, South Korean Won, Taiwan Dollar, Thai Baht, Vietnamese Dong. **Latam**: Argentine Peso, Argentine Unidades de Valor Adquisitivo, Brazilian Real, Chilean Peso, Chilean Unidad de Fomento, Colombian Peso, Peruvian Sol. **Nordics**: Danish Krone, Icelandic Krona, Norwegian Krone, Swedish Krona. **Oceania**: Australian Dollar, Fijian Dollar, New Zealand Dollar. **Other**: Canadian Dollar, Czech Koruna, Deutsche Mark, Hungarian Forint, Kazakhstani Tenge, Polish Zloty, Romanian Leu, Russian Ruble, Turkish Lira, Ukrainian Hryvnia.

[1] For a detailed overview visit `https://www.bis.org/statistics/about_securities_stats.htm`

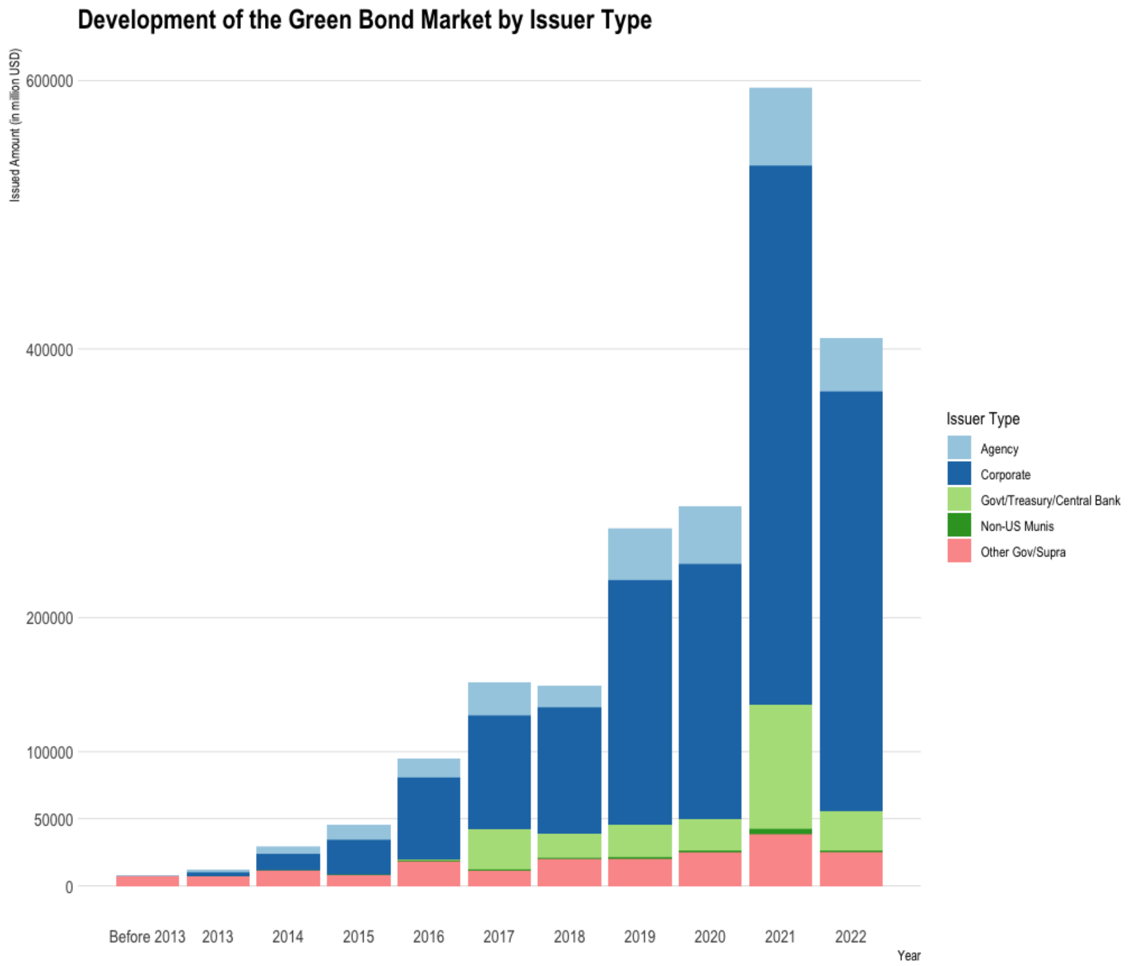



Figure 2.2: Green Bond Market Evolution by Type of Issuer (own illustration).

**Source**: Eikon Refinitiv Green Bond Universe.

## 2.2 Greenium

In 2016, first anecdotal evidence[2] emerged that, at least in some markets, green bonds were fetching better prices than regular "vanilla" bonds. This phenomenon has been coined "greenium". The implication is that green bonds have a higher price and lower yields due to the inverse relationship between bond prices and yields. For the issuer, i.e. the debtor of the bond, this is advantageous because it means a lower cost of capital. However, for the investor who buys the green bond at a higher price, this means foregoing a lower price for conventional bonds, assuming

[2]See e.g. Barclays [2015].

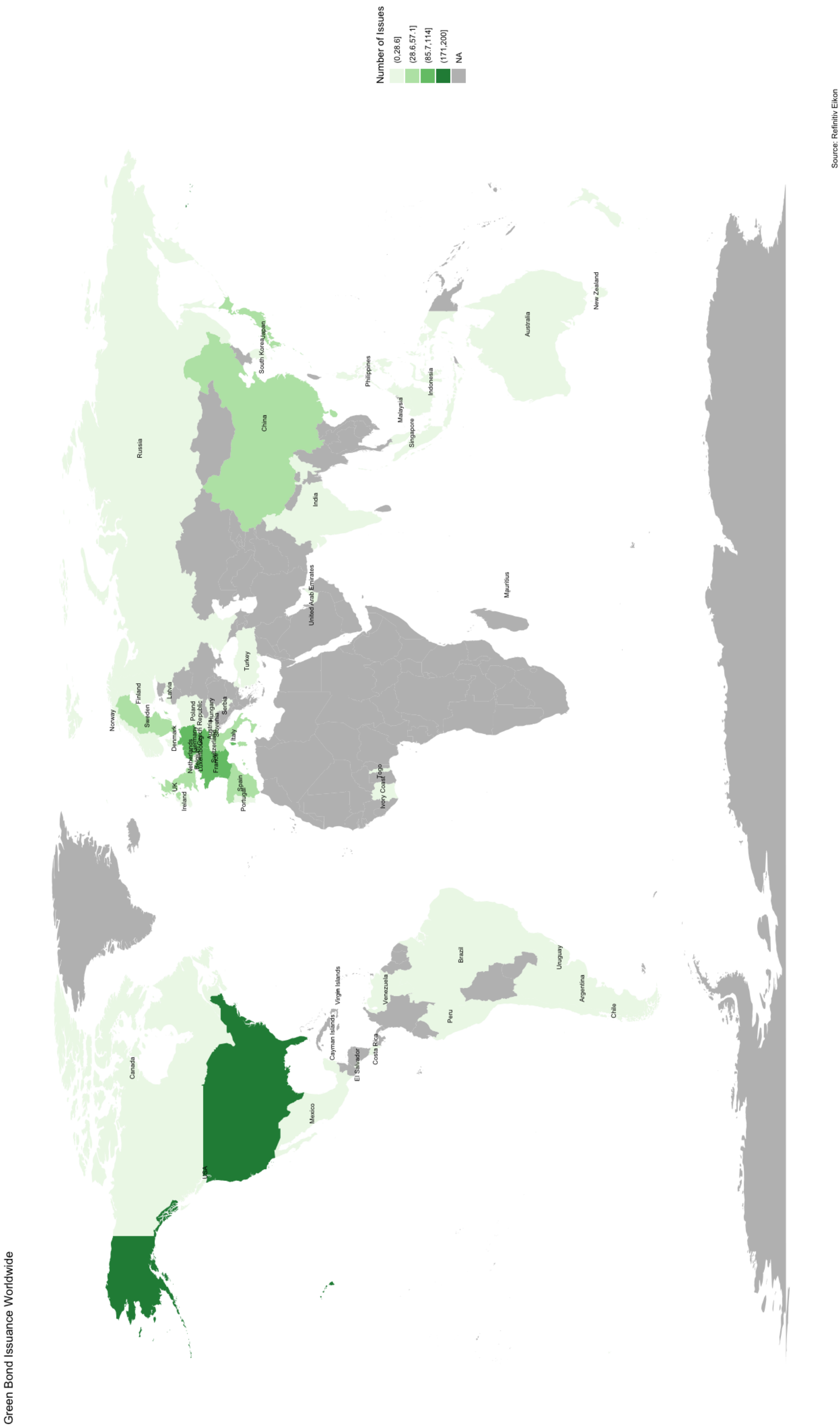



Figure 2.3: Global Heatmap of Amount of Green Bonds Issued by Country (own illustration).

that there is no difference between green and conventional bonds except for the green flag [CBI, 2016, p. 19]. Taking into account standard finance theory, where only the trade-off between risk and return plays a role in an investor's decision-making process, an investor's willingness to pay a higher price for a green bond would be irrational. In addition, it can be observed in the bond market that vanilla bonds are usually somewhat cheaper than seasoned bonds of the same issuer. This so-called new issue premium is sponsored by the issuer to attract investment [CBI, 2017, p. 10].

A capital market essentially comprises both primary and secondary markets. However, this study is exclusively concerned with the primary market. Therefore, the next paragraph summarizes the literature that has emerged since 2016 on whether the greenium exists in the primary market for green bonds and, if so, what the determinants are.

## 2.3 Literature Review

The first study to empirically test the anecdotal evidence of a greenium was conducted in 2016 by the Climate Bonds Initiative (CBI), an international organisation that works to mobilize global capital for climate action. In the primary market analysis, their sample consisted of 10 U.S. Dollar green bonds and 4 Euro green bonds issued between January 2016 and March 2017. They analyzed the yield curve of these 7 corporate green bond issuers individually and their results showed that (1) 6 bonds were priced within their own yield curve, indicating that there exists a greenium (no issuance premium), (2) 4 bonds were priced on their own yield curve, indicating the absence of a new issue premium, and (3) 4 bonds were priced outside their own yield curve suggesting the presence of a new issue premium. In summary, the findings show no difference between the issue prices of green and brown bonds [CBI, 2017, p. 10].

In a study conducted by the Bank for International Settlements, Ehlers & Packer [2017] compared credit spreads[3] on the issuance of a cross-section of 21 green bonds issued between 2014 and 2017 with credit spreads on the issuance of plain vanilla bonds of the same issuers at the nearest possible issue date. More specifically, the sample was limited to pari-passu bonds with a maturity of at least two years, a par value of $10 million and denomination in U.S. dollars or euros. The results show that, compared to conventional bond spreads, green bond spreads are, on average, 18 basis points lower. In addition, green bonds with lower issuer ratings carry wider spreads. The authors conclude that the results are consistent with the fact that demand for green bonds is high relative to supply and that lower issuer ratings imply higher credit risk. However, the results should be taken with a grain of salt, as the more detailed assessment shows some variability in the results, with a standard deviation of 27 basis points [Ehlers & Packer, 2017, pp. 97–98].

Although the following paper analyzes the secondary market, it is crucial for further research from a methodological point of view. To our knowledge, Zerbib [2017] is the first scientific

[3] Spread of yield at issuance - yield curve of U.S. Treasury security.

paper to investigate the existence of greenium. He applies a matching method, also termed the model-free approach or direct approach, which is commonly used in later studies. The matching method involves finding a pair of instruments with the same characteristics, except for the characteristic of interest, in order to quantify its effects. The advantage of this method over the standard toolkit of regressions with an appropriate specification is that we can easily encounter problems, for instance, when there are too many covariates, which can result in collinearity, lack of data, and lack of robustness. Such a situation is particularly aggravated in a setting with a small number of observations, which is often the case in green bond analysis [p. 10]. In Zerbib's matching method, a green bond is paired with a synthetic conventional bond that has exactly the same characteristics (i.e. same issuer, currency, rating, bond structure, seniority, collateral and same coupon type). Since exact maturity matching is not possible, Zerbib allows for the maturity of the conventional bonds to be two years shorter or two years longer than the green bond. Based on this universe of matching bonds, he selects the pair with the closest maturity. In addition, only conventional bonds whose issue volume is at least one quarter that of a green bond are eligible, and only conventional bonds whose issue date is no more than six years before or after the issue date of the green bond are considered. After this matching procedure, the maturity bias between the green bond and the synthetic bond is eliminated. A synthetic bond is actually a synthesis of two conventional bonds, which is why it is often referred to as a bond triplet. To eliminate the maturity bias, Zerbib uses conventional bond yields to linearly interpolate or extrapolate them at the green bond's maturity date to obtain a synthetic conventional bond yield that mimics the green bond's characteristics. If the term to maturity of the green bond is shorter or longer than the term of both conventional bonds, extrapolation is used. In all other cases, interpolation is used [pp. 12ff.].

PARTRIDGE & MEDDA's study builds on the idea of yield curve analysis from CBI [2017]. They conducted the first study in this field to quantify the greenium in the primary municipal bond market [p. 3]. Based on 50 series of municipal bonds issued between June 2013 and January 2018, green and conventional bond pairs were matched against one another based on the same issuer, use of proceeds, issue date, maturity date, and coupon, resulting in a total of 521 pairs [p. 5]. To obtain the yield curves, the authors utilized the Svensson technique [p. 8]. Their results show that between 2014 and 2016, vanilla bonds were sold at a premium, while green bonds were sold at a discount. However, in 2017, the situation reversed and green bonds were sold at a 1 basis point premium [p. 12]. In terms of spreads, the overall weighted average greenium was 4 basis points overall, with an upward trend [p. 16].

The following study is the first and one of the few to embed its analysis in a theoretical framework. BAKER ET AL. [2018] derive an asset pricing framework to understand how non-pecuniary objectives affect prices and portfolio choice.[4] The model's prediction is twofold: (1) Securities with positive environmental scores have lower expected returns [p. 1] and (2) have more concentrated ownership, particularly for those with low market values and low risk [p.

[4]The predictions derived are similar to FAMA & FRENCH [2007] who model the "taste" effects on asset prices.

28]. For their empirical analysis, the authors examine the U.S. corporate and municipal green bond markets. The corporate bonds are restricted to a sample of bonds issued between 2014 and 2016, while the municipal bonds sample includes bonds issued between 2010 and 2016 [p. 6]. BAKER ET AL. [2018] employ OLS regressions with fixed effects such as month, issuer, and yield curve. The results show the same overall pattern in all specifications: green bonds are sold at a moderate premium. Another result worth noting is that CBI-certified green bonds commanded a higher premium than non-certified CBI green bonds [pp. 21ff.]. Moreover, the analysis supports the second prediction of their framework that green bond ownership is more concentrated. This applies in particular to bonds with a low nominal value and low risk (high rating) [p. 32].

GIANFRATE & PERI [2019] contribute to the literature by adopting a propensity score matching (PSM) methodology to quantify the average treatment effect on the treated (ATT). The sample consists of bonds issued between January 2007 and December 2017. Only fixed coupon bonds, euro-denominated bonds with an issuance volume of at least EUR 200 million, and all bonds with a rating above BBB- were eligible. The final sample consists of 121 green bonds. The PSM method allows the estimation of the counterfactual condition, i.e., the unobservable condition that a green bond is not green. To obtain the most accurate estimate, a control group (conventional bonds) is required that is identical in all respects to the treated group (green bonds) except for the treatment attribute. Since such a situation is not achievable, one would focus on the control group, that is as similar as possible to the treated group. The methodological procedure is as follows: (1) estimate the propensity score by predicting the probability that a bond is green (using either a Logit or Probit function) and (2) match treated units and control units based on the propensity score by using the nearest neighbors matching (NN) algorithm. Finally, calculate the average treatment effect of the treated (ATT).[5] The results show a highly significant (1% level) estimate in all comparison groups, ranging from -14.8 to -19.4 basis points. This suggests that, on average, green bonds offer investors a lower return than their conventional counterparts. Moreover, if the issuer is a corporation (operating primarily in the utilities and energy sectors), the average advantage is -21 basis points, while it is lower at -15 basis points for non-corporation issuers [pp. 128ff.].

The next paper is from LARCKER & WATTS [2020], who examine the U.S. municipal bond market from June 2013 to July 2018, very similar to PARTRIDGE & MEDDA. However, LARCKER & WATTS [2020] use a simple matching procedure in which they select (non-callable) bonds that were issued by the same issuer on the same day that have the same rating, coupon, and a maximum maturity difference of one year. For their final sample of 640 matched pairs, they calculate the average treatment effect (ATE).[6] [pp. 7ff.] Using kernel density estimates of differences, paired t-tests, and Wilcoxon tests, their results show a statistically significant difference of about 0.4 basis points of yield difference, suggesting that green bonds are sold at a discount. However, the magnitude is economically insignificant and the results seem to be driven by outliers. Therefore, the authors conclude that the yield differential is exactly zero, which is in contrast to the results

[5] ATT$= \mathrm{E}[Y^1 - Y^0 \mid D=1] = \mathrm{E}[Y^1 \mid D=1] - \mathrm{E}[Y^0 \mid D=1]$.
[6] ATE $= \hat{\tau} = \frac{1}{N}\sum_{i=1}^{N}(Y_i^G - Y_i^{NG})$

of PARTRIDGE & MEDDA [pp. 10ff.].

TANG & ZHANG [2020] construct the most comprehensive international green bond dataset for the period June 2007 to July 2017, using an OLS regression with fixed effects by month, country, or issuer. The specification with country fixed effects as the sole factor yielded a significant greenium at the 5% level. Issuer and month fixed effects were not statistically significant [p. 5; p. 11].

The following two paragraphs present studies that shed light on the presence of a greenium in the Chinese bond market. First, WANG & LI [2020] use a dataset of all green corporate bonds issued in mainland China from 2016 to 2020 Q2, which corresponds to 324 green bonds [p. 3]. Using the strict matching approach of LARCKER & WATTS [2020] and the paired t-test as well as the Wilcoxon test, the authors find no difference in mean and median returns between green and conventional bonds [pp. 5f.]. Second, SHENG ET AL. [2021] use a sample of all bonds issued on the Shanghai and Shenzhen stock exchanges and the interbank bond market from 2016 to 2018. They use propensity score matching with nearest neighbor matching to estimate the average treatment effects for the green bond (ATT). Depending on the specification, the ATT ranges from -0.37 to -0.22, but is highly significant at the 1% threshold in all cases. As for the average difference between the issue yield of green and conventional bonds, the results show that it is -7.8 basis points for the whole sample. However, this result is due to the high mean value of the financial issuers, which amounts to -22.2 basis points. In addition, green bonds issued by state-owned enterprises (SOEs) have on average a higher greenium than non-SOEs [pp. 2644ff.].

AGLIARDI & AGLIARDI [2021] provide the literature with a theoretical model of optimal portfolio allocation that can capture both a negative and a positive premium. The numerical simulation results are as follows: (1) the greenium becomes narrower when interest rates are lower, (2) uncertainty about the effectiveness of the green investment is negatively related to the greenium, (3) more effective technology increases the greenium, (4) volatile asset prices positively affect the greenium, (5) tax rates and greenium go in the same direction, and (6) the greenium is larger when the introduction of the green project directly benefits the core business, otherwise the greenium may even reverse its sign [pp. 271–272].

Correspondingly, KAPRAUN ET AL. [2021] develop a theoretical model, but in a microeconomic way. According to this model, households prefer green bonds with environmental impacts and are willing to pay a higher price for them than for bonds without environmental impacts. Moreover, households are willing to pay a higher price for green bonds issued by companies with a lower reputation for sustainability than for green bonds issued by companies with high environmental standards [p. 15]. To test the predictions, the authors collect a large green bond dataset of 2099 green bonds issued between January 2009 and February 2021 [p. 17]. As a first step, the study runs a fixed-effects OLS regression that yields an average of 12.8 basis points lower return for green bonds than for conventional bonds. However, when controlling for creditworthiness, this effect disappears. When the green bond is certified, there is a significant greenium of 16 basis points. Interestingly, 90% of euro-denominated green bonds and 80% of large green bonds are certified. Consequently, these specifications yield significant greeniums. Finally, green bonds issued by governments and supranational organizations command high premiums of about 18.5 basis points, while corporate bonds trade at significant discounts of about 6 basis points. Thus, the credibility of green projects seems to be an important factor explaining the presence of greenium [pp. 24ff.]. In a second step, KAPRAUN ET AL. [2021] use the matching method of ZERBIB [2017], but with stricter bounds on maturity and issue size [pp. 17–18]. The yield difference of the 658 matched bonds shows that the issue yield of green bonds is on average 7.2 basis points lower than that of conventional bonds. Nevertheless, the authors conclude that their results show insignificant greenium on average [p. 29].

LÖFFLER ET AL. [2021] also use a large dataset of green bonds issued between 2007 and October 2019 [p. 6]. Similar to GIANFRATE & PERI [2019], they use a PSM method. As an extension, they also use Coarsened Exact Matching (CEM), which is arguably a better approach than PSM because it reduces model dependence as well as covariate imbalances between treated and controls [pp. 10f.]. Their analysis shows that green bond ask yields in the non-matching sample are 15 basis points lower than their counterparts. In the matched samples, the range of ask yields amount to 16-24 basis points [p. 14].

A very recent study that develops a theoretical model to explain greenium is the working paper by DAUBANES ET AL. [2021]. The authors derive a signaling model that captures the rationale behind managers' incentives to engage in CO2-reducing projects through certified green bonds [p. 6]. In a nutshell, their model derives an equilibrium condition in which the stock market reaction to a company's green bond issuance is positive. Therefore, managers constrain green bond issuance such that the stock market response remains positive. Moreover, this effect is amplified by carbon prices [p. 16ff.]. This is explained by the fact that green bonds are complementary to carbon prices. However, the authors conclude that this effect is probably due to a short-lived financial interest [p. 33].

The next study is again an empirical study covering green bonds issued globally between 2007 and 2018. FATICA ET AL. [2021] identified a total of 1397 green bonds for which they used the OLS fixed effects econometric strategy, which is very similar to BAKER ET AL. [2018] [pp. 5–6]. They arrive at the following results: Compared to ordinary bonds, only green bonds issued by supranational institutions and non-financial corporations sell at a premium. For instance, the premium for the former amounts to 80 basis points (1% level), while for the latter it is 20 basis points (5% level). For financial corporations, the difference in yield is not statistically significant. Moreover, the greenium for self-labeled green bonds is on average lower compared to externally reviewed bonds. The yield differential for one-time green bond issuers is also lower than for repeat issuers [pp. 6ff.].

Last but not least, CARAMICHAEL & RAPP [2022] also employ a fixed effects OLS regression on a dataset of 1169 green bonds issued between 2014 and 2021 [p. 3]. The following restrictions apply: Only fixed- or zero-coupon bonds issued in euros or U.S. dollars by private or state-owned companies with a notional value of at least USD 500 million are eligible [p. 8]. Their analysis shows a greenium of 8 basis points [p. 12]. Moreover, green bonds that are oversubscribed fetch a higher greenium. Specifically, a 1% increase in oversubscription leads to a 0.058 basis point increase in the greenium. This idea that increased demand drives the greenium is also confirmed by controlling for the inclusion in a green bond index [pp. 17–18]. The authors conclude with the following finding: *"While U.S. dollar- and euro-denominated green bonds capture comparable greeniums, we find that the greenium is allocated primarily to local euro and foreign U.S. dollar issuers. While green bond governance and external review appear to matter for the greenium, the credibility of the underlying projects does not have a significant impact. Instead, the greenium is unevenly distributed to large, investment-grade issuers, primarily within the banking sector and developed economies [p. 24]."*

CHAPTER 3

# METHODOLOGY

## 3.1 Dataset

In this section, we describe the data gathering process. In this paper, we use the Eikon Refinitiv database. We extract all available bond data between January 01, 2008 and September 26, 2022 and follow the literature by filtering bonds by issue amount (> USD 500 million)[1] [CARAMICHAEL & RAPP, 2022, p. 8], coupon type (fixed rate only), and time to maturity (>1 year). The first and third criteria are relevant to bypass controlling for liquidity premia in the analysis. Similarly, restricting the data to fixed coupon bonds reduces complexity and also mitigates later issues of unobservable confounding due to uncertainty [GIANFRATE & PERI, 2019, p. 128].

Table 3.1: Eikon Refinitiv Search Criteria

| **Criteria** | **Description** |
|---|---|
| Issuance Date | 01. Jan 2008 - 26 Sep 2022 |
| Sustainable Finance Flag | True/False |
| Transaction Status | Live, Redeemed |
| Principal Amount | ≥ USD 500'000'000 |
| Issue Type | Agency, Supranational, Sovereign, Emerging Market Corporate, Federal Credit Agency, High Yield Corporate, Investment Grade Corporate |
| Coupon Type | Fixed Rate |
| Private Placement Flag | False |

### 3.1.1 Variables

With the exception of two variables, all variables described in Table 3.2 were taken from the Eikon Refinitiv deal screen database. These two variables are ESG bond type and seniority. We

[1]This contrasts with LÖFFLER ET AL. [2021]'s study, which applies the filter at USD 200 million.

collected them by accessing a database through the formula builder of the Refinitiv Excel plugin using the ISINs of the bonds. As for ratings, we could only obtain this information from Moody's. Unfortunately, ratings from S&P and Fitch were not available under the license. Finally, our universe data set consists of 14 potential covariates, an outcome variable, i.e., the offer yield to maturity, and a treatment variable, i.e., the green flag.

### 3.1.2 Data Cleaning

Table 3.3 describes the cleaning process. We did our best to minimize missing green bond values by manually adding values from the Bloomberg database. The list of ISINs for which we have added this data can be found in the appendix (7). Moreover, we found a highly implausible value of the outcome variable (offer yield to maturity) amounting to 99.852% which we adjusted for the true value. Our final sample, which we refer to as our universe, consists of 1'065 green bonds and 11'331 brown bonds. Based on this dataset, we form three subsamples, which we will explain in more detail after describing the variables in the next section.

### 3.1.3 Subset

To leverage the potential of our dataset and to assess the research question more precisely in terms of robustness, we formed three subsamples. First, based on our original so-called universe dataset, we constructed a subsample that includes only issuers that have issued both green and conventional bonds. This eliminates the need to control for each issuer in the analysis. Second, we drew two different subsamples based on the first subsample. First, to further control for liquidity issues due to small bond markets, we included bonds denominated in euros and U.S. dollars in the subsample. These two currencies account for 90% of the total green bond market. On the other hand, we drew a subsample based on the variable "ESG bond type" to include only green bonds that are either aligned or certified by the CBI. This allows us to analyze whether these bonds are valued differently. These types of bonds account for 58% of the green bonds in our first subsample.

Table 3.2: Variable Description

| Variable name | Binary | Type | Description |
|---|---|---|---|
| Issue Date | No | C | Date of Issuance; Years: 2008-2022 |
| Maturity Date | No | C | Date of Maturity |
| Time to Maturity (Days) | No | C | Date of Maturity − Date of Issuance (in days) |
| Issuer | Yes | C | Name of Issuer |
| Issuer Type | Yes | C | Type of Issuer: Dummy equal to 1 (Public sector) for bonds issued by agency, supranational, sovereign or federal credit agency. Otherwise 0 (Private sector) for bonds issued by investment grade corporates, emerging market corporates or high yield corporates |
| Issued Amount | No | C | Amount of Issuance |
| TRBC Economic Sector | Yes | C | Academic & Educational Services, Basic Materials, Consumer Cyclicals, Consumer Non-Cyclicals, Energy, Financials, Government Activity, Healthcare, Industrials, Institutions, Associations & Organizations, Real Estate, Technology, Utilities |
| Coupon Rate | Yes | C | Coupon in Percentage |
| New Issues Rating (Moody's) | Yes | C | Rating conversion: AAA = Aaa; AA = Aa1, Aa2, Aa3; A = A1, A2, A3; BBB = Baa1, Baa2, Baa3; BB = Ba1, Ba2, Ba3; B = B1, B2, B3; CCC = Caa1, Caa2, Caa3 |
| Currency | Yes | C | Australian Dollar (AUD), Braziliean Real (BRL), Canadian Dollar (CAD), Chilean Peso (CLP), Chinese Yuan Renminbi (CNY), Colombian Peso (COP), Croation Kuna (HRK), Euro (EUR), Great Britain Pound (GBP), Hong Kong Dollar (HKD), Japanese Yen (JPY), Kazhakstan Tenge (KZT), Mexican Peso (MXN), New Zealand Dollar (NZD), Norwegian Krone (NOK), Peruvian Nuevo Sol (PEN), Philippine Peso (PHP), Russan New Ruble (RUB), Singapore Dollar (SGD), Swedish Krona (SEK), Swiss Franc (CHF), Thai Baht (THB), New Turkish Lira (TRY), U.S. Dollar (USD), Uruguayan Peso Uruguayano (UYU) |
| Guarantor | Yes | C | Dummy equal to 1 if bond is secured by any kind of the following credit enhancement types: Guaranteed by an Entity, Insured, Keep Well Agreement, Letter of Credit, Line of Credit, Liquidity Agreement, Purchase Agreement, State Sponsored or Support Agreement; 0 else |
| Coupon Payment Frequency | Yes | C | Annual Coupon, Semi Annual Coupon, Quarterly, Monthly |
| Seniority | Yes | C | First-Lien Loan, First Mortgage, First Refunding Mortgage, Second-Lien Loan, Junior Subordinated, Senior Secured Mortgage, Refunding Mortgage, Senior Secured, Senior Unsecured, Senior Non-Preferred, Senior Preferred, Senior Secured, Subordinated Unsecured, Subordinated Secured |
| Offer Yield to Maturity | No | O | Yield offered to Investors at Issuance in Percentage |
| ESG Bond Type | Yes | C | CBI aligned green bond, CBI certified green bond, No ESG, Not disclosed, Self-labelled |
| Green Flag | Yes | T | Dummy equal to 1 if green bond; 0 else |

Type: C = Covariate; O = Outcome; T = Treatment

Table 3.3: Data Cleaning Process

| | # Green Bonds | | # Brown Bonds |
|---|---|---|---|
| Total | 1’686 | Total | 37’076 |
| Missing Issuance Date | -126 | Total Missing Values | -25’745 |
| Perpetual Maturity | -2 | | |
| Time to Maturity <1 year | -78 | | |
| Missing Yield at Issuance | -13 | | |
| Duplicates | -49 | | |
| Missing Moody’s Rating | -317 | | |
| | **1’065** | | **11’331** |

## 3.2 Methods

### 3.2.1 Causal Inference Framework

We start by defining some common notations. Each unit in the dataset will be represented by:

1. $X_i$ : is a $K$-component vector of features, i.e. covariates, known not to be affected by the treatment;
2. $D_i \in \{0,1\}$ : is a binary variable indicating whether the individual was treated (1) or not (0);
3. $Y_i^{\text{obs}} \in \mathbb{R}$ : is the observed outcome for that individual.

To isolate the causal effect, one must look for a convincing ceteris paribus comparison. This is why causal statements involve counterfactual comparisons, i.e., what would have been observed for the same unit under a different treatment. To express this mathematically, this study uses the notion of potential outcome, as first formulated by RUBIN [1974]:

1. $Y_i(1)$ : the outcome unit $i$ would attain if they received the treatment;
2. $Y_i(0)$ : the outcome unit $i$ would attain if they were part of the control group.

Obviously, we can only observe one of these two potential outcomes for each unit. Indeed, we can observe either the realization of $(X_i, Y_i(0))$ for the control units or $(X_i, Y_i(1))$ for the treated units, while the other potential outcome is always unobservable. This is what is called the “fundamental problem of causal inference”. The goal of causal inference is therefore to predict these counterfactuals, in order to estimate the average treatment effect as an expectation of the difference between the two:

$$\text{ATE} = \text{E}[Y_i(1) - Y_i(0)] \tag{3.1}$$

If one wishes to estimate the treatment effect for specific subgroups within a population, it can be obtained by conditioning on a set of covariates. When the treatment effect is heterogeneous with respect to these covariates, this heterogeneity can be captured by (the expectation of) the conditional distribution of the random variable $Y_i(1)-Y_i(0)$ on the vector of covariates X. This conditional expectation is called the conditional average treatment effect, or CATE and is expressed as:

$$\begin{aligned} \text{CATE}(x) &= \text{E}[Y_i(1)-Y_i(0) \mid X=x] \\ &= \text{E}[Y_i(1) \mid X_i = x] - \text{E}[Y_i(0) \mid X_i = x] \\ &= \text{E}[Y_i \mid X_i = x, D=1] - \text{E}[Y_i \mid X_i = x, D=0] \\ &= \mu_1(x) - \mu_0(x) \end{aligned} \tag{3.2}$$

However, the data alone are not sufficient to predict the counterfactual outcome. To identify the effects of interest, we require a set of identification assumptions. These assumptions depend on a particular study design. In our case, the data are observational, as the treatment was not randomly assigned to the study population, but only observed. Thus, the selection-on-observables design comes to the fore. In this setting, it is very probable that companies that issue green bonds are systematically different from companies that do not issue green bonds. To account for this unequal comparison, the selection-on-observables strategy assumes that we observe and adjust for all relevant confounders, i.e., all covariates $X_i$ that jointly affect both treatment $D_i$ and potential outcomes $Y_i(0)$ and $Y_i(1)$.

1. **Assumption: Unconfoundedness**. This condition requires that potential outcomes are conditionally independent of treatment for any given value of the confounding variables. In other words, once we condition on the observable characteristics, the treatment assignment is independent of how each individual would respond to the treatment. Mathematically, this can be expressed as follows:

$$Y_i(1), Y_i(0) \perp D_i \mid X_i = x. \tag{3.3}$$

   where $\perp$ stands for independence. The assumption of unconfounded assignment is always valid in randomized experiments, or when all confounding variables, i.e., variables that jointly influence the outcome Y and the treatment, are observable and included in the model. Finally, it is also known as the conditional independence assumption (CIA).

2. **Assumption: Overlap or Common Support**. For any given value of the confounding variable, one unit could potentially be observed in both treatments. Indeed, to estimate the treatment effect for a unit with particular characteristics $X_i = x$, we must ensure that we can observe treated and untreated individuals with these same characteristics. Since causal effects are based on the comparison of units with the same characteristics but different treatments, they ensure that such units exist. Mathematically, it can be written as:

$$\forall x \in \text{supp}(X), \quad 0 < P(X=1 \mid X=x) < 1. \tag{3.4}$$

In other words, we need to ensure that any observation, regardless of its covariate values, has a chance of being assigned to either the treated or control group.

3. **Assumption: SUTVA**. This assumption is known as the stable unit treatment value assumption and states that the observed treatment value for one unit is independent of the treatment exposure for other units, ruling out any general equilibrium or spillover effects between treated and control units. Mathematically, it can be expressed as follows:

$$Y_i = W_i \cdot Y_i(1) + (1 - W_i) \cdot Y_i(0). \tag{3.5}$$

   Moreover, this assumption also implies the condition that there are no hidden variations in treatment for each unit.

4. **Assumption: Exogeneity**. This last assumption requires that the covariates are not influenced by the treatment, again mathematically formulated as follows:

$$X_i(0) = X_i(1). \tag{3.6}$$

### 3.2.2 Causal Machine Learning: Causal Forest

Causal Forests build on the idea of Random Forests (Breiman [2001]). These machine learning methods seem remarkably effective in prediction contexts. However, good performance in prediction does not necessarily mean good performance in estimation or in inference on "causal" parameters. To enable these methods for a causal framework, scientists have developed techniques consistent with theory to avoid bias in estimation. Our paper builds on the methods developed by Athey et al. [2019] and Wager & Athey [2018]. These causal forests are a specialization of the generalized random forest algorithm with the goal of estimating the conditional average treatment effect (CATE). Its implementation is motivated by the R-learner Nie & Wager [2017], i.e., a meta-algorithm using the idea of orthogonalization to cancel any feature selection bias (regularization bias) [Athey et al., 2019, p. 5]. In the following paragraphs we will describe the basic idea of this method.

The idea of Causal Forest is to construct and average many different deep Causal Trees. While deep trees often have low bias but high variance in their prediction, averaging over many trees largely reduces the variance while keeping the bias low. To ensure that individual trees are sufficiently different, each tree is created from only a random subsample of observations and a subsample of covariates. When each individual tree in the forest is estimated honestly, the causal forest estimates are unbiased and have valid confidence intervals. A method is honest if it uses one subset of the data to estimate the model parameters and another subset to produce estimates based on those estimated parameters. The Causal Forest allows us first to estimate the heterogeneity of causal effects and then to make inferences about the magnitude of differences in treatment effects, i.e., to test hypotheses about differences in effects across subpopulations.

In mathematical terms, suppose that we have a training set $\{(X_i, Y_i, W_i)\}_{i=1}^n$, a test point $x$, and a tree predictor $T$:

$$\hat{\tau}(x) = T\left(x; \{(X_i, Y_i, W_i)\}_{i=1}^n\right)$$

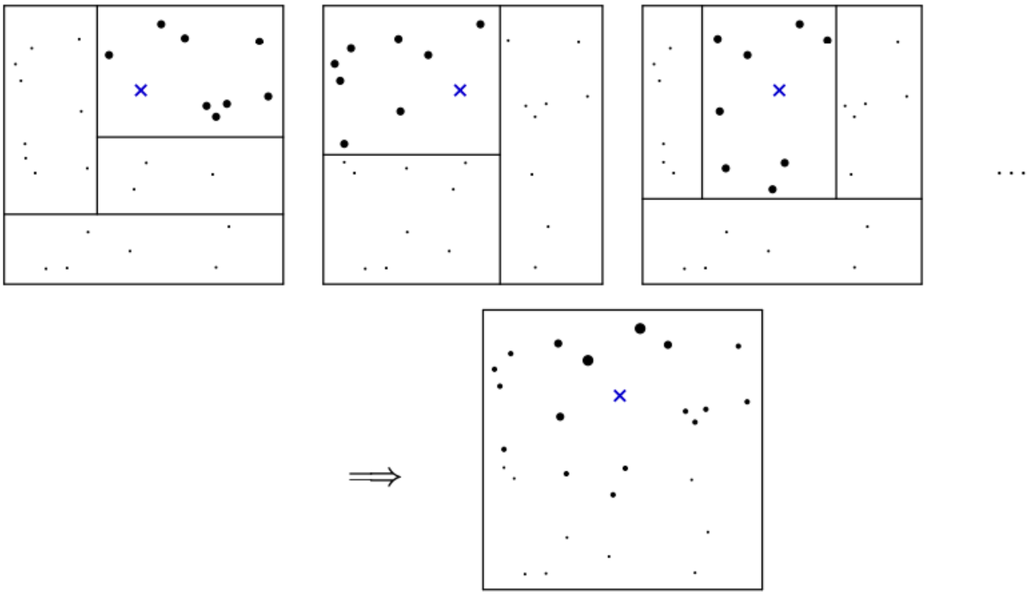


Figure 3.1: Illustration of the Random Forest weighting function. Reprinted from ATHEY ET AL. [2019, p. 6].

We can replace the tree predictor by building and averaging many different trees $T^*$:

$$\hat{\tau}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b^*\left(x; \{(X_i, Y_i, W_i)\}_{i=1}^n\right)$$

In addition to this "ensemble" way of thinking, where a Random Forest prediction is an average of the predictions of the individual trees, we can also think of Random Forests as an adaptive kernel method [ATHEY & WAGER, 2019, p. 5]:

$$\hat{\tau}(x) = \sum_{i=1}^{n} \alpha_i(x) Y_i, \quad \alpha_i(x) = \frac{1}{B}\sum_{b=1}^{B} T_b^*\left(x; \{(X_i, W_i)\}_{i=1}^n\right), \tag{3.7}$$

where $\alpha_i(x)$ is a data-adaptive kernel that measures how often each training sample falls in the same leaf as the test point x [ATHEY & WAGER, 2019, p. 5]. This weighting approach is illustrated in Figure 3.1.

The implementation of the Causal Forest method in R is provided by the *grf* (generalized random forest) package. For the estimation of the average treatment effect (ATE), the package applies the augmented inverse probability weighting (AIPW) method, which is a doubly-robust estimator. Using the propensity score $e(x) = P[W_i \mid X_i = x]$ and the response function $m(x) = E[Y_i \mid X_i = x]$, the ATE is consistent when either function is consistent. Further, if the conditional average treatment function is constant, i.e. $\tau(x) = \tau$ for all $x \in \mathcal{X}$, we can write the estimator mathematically as follows [ATHEY & WAGER, 2019, p. 4]:

$$\hat{\tau} = \frac{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{m}(X_i))(W_i - \hat{e}(X_i))}{\frac{1}{n}\sum_{i=1}^{n}(W_i - \hat{e}(X_i))^2} \tag{3.8}$$

Finally, beyond the assumption presented in the previous subsection, this method requires that the data are independently and identically distributed (i.i.d) ([Athey & Wager, 2019, p. 4].

### 3.2.3 Matching

Matching is an increasingly popular method for controlling observed confounding variables when estimating causal effects in non-experimental studies. The purpose is to guarantee that there are no large differences in the distribution of the observed covariates in the treatment and comparison groups, as would be the case if a randomized experiment were conducted [Stuart & Green, 2008, p. 2]. Thus, if the distributions are sufficiently similar, this should result in little bias in the estimated treatment effect [p. 9]. In an optimal scenario, one would require perfect matches between treatment and comparison groups. Although such a method, i.e., exact matching, exists, it is rarely feasible because it would require a data set with a vast number of observations and relatively few confounding variables [Békés & Kézdi, 2021, p. 602]. In the following subsections, we briefly summarize the propensity score matching approach.

Prior to this, it is worth mentioning the four steps of implementing matching methods, as described by Stuart [2010, pp. 5ff.]:

1. Defining "closeness": the distance measure used to calculate whether a treated observation closely matches an untreated observation. (E.g., Exact, Mahalanobis, Propensity Score etc.);
2. Implementing a matching method. (E.g. Nearest neighbour, Subclassification etc.);
3. Quality Assessment (i.e. balance checks): possibly re-iterating step (1) and (2) until a well-matched (well-balanced) sample is obtained;
4. Analysis of the outcome and estimation of treatment effect.

#### Propensity Score Matching

As the name suggests, the basic idea of this method is to estimate a propensity score, i.e., a single scalar, defined mathematically as follows:

$$e_i(X_i) = Pr[D_i = 1|X_i] \tag{3.9}$$

The equation reads: the propensity score is the conditional probability of being treated for each observation in the data, given all confounder variables. Estimating such a probability model is straightforward, using either a logit or probit model. To match the treated observations and the control observations based on their similarity in propensity scores, one can use the most widely used matching procedure called nearest neighbor matching [Békés & Kézdi, 2021, p. 604]. In its most basic form, the so-called 1:1 nearest neighbor matching algorithm selects the control observation $j$ with the smallest distance between it and the treated observation $i$ for each treated observation. Mathematically, this can be expressed as follows [Wooldridge, 2010, p. 936]:

$$h(i) = \text{argmin}_h |\hat{e}(x_j) - \hat{e}(x_i)| \tag{3.10}$$

However, this approach may result in poor matches if, for instance, no control observation has a similar propensity score to a particular treatment observation [STUART, 2010, p. 10]. In such a situation, as described by the matching process of STUART [2010] above, one should opt to iteratively choose different covariates for matching or use a different probability model until the balance checks are well-satisfied. To sum up, the propensity score matching approach suffers from some pitfalls: (1) It cannot guarantee any level of imbalance or model dependence reduction, (2) the dimensionality reduction by estimating a single scalar violates the congruence principle [IACUS ET AL., 2012, p. 2].

# Chapter 4

## Research results

### 4.1 Verification of Model Assumptions

The purpose of this section is to provide a discussion of the potential violation of the underlying assumptions in our research design.

1. **CIA**: This assumption is not statistically verifiable and therefore can only be defended in words. Given the circumstances, we did our best to include the major confounding factors that determine treatment and outcome. However, we must recognize that there may be confounding that we cannot observe. For instance, one could argue that management incentives have a critical impact on treatment and outcome. In particular, incentives that translate into marketing efforts, especially in terms of green washing.

2. **Common Support**: This assumption can be statistically tested by calculating the propensity scores for each group and visually checking whether the distribution of propensity scores overlaps in the two groups. In addition, the distributions should also have a similar shape. We show these plots in the analysis, where we also comment on whether the assumption of common support is met.

3. **SUTVA**: Using reasoning, we can test whether the following two statements are true: (1) the outcome of one observation does not depend on the treatment values of other observations and (2) there are no variations in the treatment of each observation. The first statement could be violated if an issuer has already issued a green bond and concluded that green bond issuance is financially advantageous compared to a conventional bond. If this reasoning leads to more green bonds being issued, it could have an impact on the yield (outcome) of those bonds. However, it is not clear how the overall equilibrium will adjust. We argue that for spillover effects to occur, a significant number of issuers must share the same reasoning

at the same time. With respect to the second statement, one could argue that there are different shades of green bonds and, more importantly, that the green bond labelling is not a standardized and unbiased process. However, we argue that we only measure whether a bond is green or not according to Eikon Refinitiv, which in turn relies on the CBI dataset, from which we conclude that we only consider one expert opinion. Thus, we infer that our dataset does not contain variations due to different expert opinions, thereby confirming the validity of the second statement.

4. **Exogeneity**: The last assumption of the selection-on-observables study design assumes that the covariates are not affected by the treatment. In this case, one could argue that green bonds tend to finance larger projects and have a longer-term nature than conventional bonds because of their green vision. However, in examining the numbers, we cannot confirm the hypothesis for project size. From a central tendency perspective, conventional bonds finance larger projects. On the other hand, the maturity of green bonds is on average 1.5 years longer compared to their counterparts.

5. **i.i.d Assumption**: The analysis method used in this paper is only valid under the i.i.d assumption. Due to the fact that our analysis includes the output of different issuers, we cannot assume that the offer yield to maturity follows this assumption. To examine the consequences of violating this assumption on our method, we have provided a small simulation study at the end of this chapter.

## 4.2 Descriptive Statistics

As an important preliminary note, we will present the descriptive statistics of the universe dataset only. The descriptive statistics of the subsets are presented in the appendix (18,30,50). Our universe includes a total of 11'179 bonds, of which 9.16% are green bonds (1'024). These bonds are issued by 2'177 unique issuers. Table 4.1 and Table 4.2 present the summary statistics for the numerical variables of green and brown bonds, respectively. First, we notice that the maturity of green bonds is on average 533 days ($\approx$ 1.5 years) longer than that of their brown counterpart. Second, the green bond amount issued, on average, is $\approx$ 170$ million lower than for brown bonds, and green bonds also consist of the zero-coupon type, which is not the case for brown bonds. In addition, the coupon rate for green bonds is $\approx$ 1% lower than that of brown bonds and the former can even achieve negative values. Finally, the offered yield to maturity for brown bonds is, on average, about 1% higher than for green bonds. For a more detailed analysis, we have included raincloud plots in the appendix (1).

Table 54a shows the propensities for the year of issuance. For green bonds, the same pattern is observed as in Figure 2.1: the market grows exponentially every two years until 2021. In contrast, the brown bond market has contracted after 2012 and more than halved by 2021. In addition, our dataset does not include green bonds issued in 2008. Next, in Table 54b we show the propensity table for ratings. It can be observed that most green bonds (27%) are rated triple B,

Table 4.1: Universe Green Bond Numeric Variables Summary Statistics

| Statistic | N | Mean | St. Dev. | Min | Max | | |
|---|---|---|---|---|---|---|---|
| Time to Maturity (Days) | 1,024 | 3,214 | 2,418 | 367 | 1,834 | 3,660 | 21,922 |
| Issue Amount | 1,024 | 1,290 | 1,960 | 500 | 577 | 1,179 | 33,564 |
| Coupon Rate | 1,024 | 1.644 | 1.517 | 0 | 0.5 | 2.4 | 10 |
| Offer Yield to Maturity | 1,024 | 1.688 | 1.521 | 0 | 0.5 | 2.5 | 10 |

Table 4.2: Universe Brown Bond Numeric Variables Summary Statistics

| Statistic | N | Mean | St. Dev. | Min | Max | | |
|---|---|---|---|---|---|---|---|
| Time to Maturity (Days) | 11,179 | 2,681 | 2,347.479 | 366 | 1,712 | 3,656 | 36,533 |
| Issue Amount | 11,179 | 1,463 | 1,409.418 | 500 | 674 | 1,603 | 30,089 |
| Coupon Rate | 11,179 | 2.688 | 1.961 | 0 | 1.1 | 3.9 | 20 |
| Offer Yield to Maturity | 11,179 | 2.720 | 1.969 | 0 | 1.1 | 4.0 | 20 |

while most brown bonds (36.3%) are rated triple A. Overall, both green and brown bonds in our dataset are rated at least triple B at 93.5% and 93.7%, respectively. For the remaining dummy variables, we will present the propensity tables in the appendix (5) and only briefly comment on them here. The reason is that their propensities do not show relevant large differences between green and brown bonds, so we can save some space. First, the coupon frequency with the highest frequency is the annual coupon (61% green, 58% brown) followed by the semi annual coupon (38.7% green, 41.6% brown). The industry for both types of bonds is dominated by financials (48.4% green, 68.9% brown) and succeeded by government activity (14.3% green, 17.1% brown). One important difference is that the propensity for utilities is higher for green bonds (12.5%), than for brown bonds (2%). The Euro market dominates in both bond types (56% green, 48.2% brown) followed by the Dollar market (35.9% green, 39.9% brown). Regarding seniority, senior unsecured bonds rank prominently for both bond types (72.3% green, 62.2% brown). Finally, both types of bonds are balanced in terms of issuer sector and guarantor. In the former, the corporate sector accounts for around $\frac{2}{3}$ of the pie and the public sector for around $\frac{1}{3}$, while in the latter, around 20% of bonds have a guarantor and around 80% do not.

Another important preliminary analysis should be performed with respect to correlations. Since our dataset contains too many variables to display a correlation heatmap, in Figure 4.1 we show the 10 most relevant pairs according to the highest correlation at a statistical p-value below 5%. Strikingly, we have a highly correlated pair, namely the coupon rate with our outcome variable, which is 99% correlated. Because of the high correlation, we run the risk that the Random Forest method often uses this variable as a split variable, making the Leafs no longer heterogeneous and driving the effect to zero. Indeed, the analysis showed that the majority of splits are caused by the coupon rate, and adjusting the hyperparameters did not solve the problem.[1] Due to the fact that the coupon rate is very closely related to the offer yield to maturity

[1] We do not report this result in this paper. However, one can increase the number of *mtry*. This hyperparameter

| Issue Year | Green (%) | Brown (%) |
|---|---|---|
| 2008 | 0.0 | 5.9 |
| 2009 | 0.3 | 9.0 |
| 2010 | 0.5 | 8.4 |
| 2011 | 0.0 | 7.9 |
| 2012 | 0.7 | 9.3 |
| 2013 | 1.4 | 7.6 |
| 2014 | 1.0 | 7.6 |
| 2015 | 3.7 | 7.4 |
| 2016 | 4.5 | 6.8 |
| 2017 | 6.5 | 6.2 |
| 2018 | 7.7 | 5.6 |
| 2019 | 11.7 | 6.3 |
| 2020 | 16.6 | 4.7 |
| 2021 | 27.1 | 3.9 |
| 2022 | 18.3 | 3.4 |

(a) Issue Year

| Rating | Green (%) | Brown (%) |
|---|---|---|
| AAA | 24.70 | 36.30 |
| AA | 18.00 | 22.50 |
| A | 23.80 | 18.90 |
| BBB | 27.00 | 16.00 |
| BB | 4.80 | 3.90 |
| B | 1.50 | 2.10 |
| CCC | 0.02 | 0.03 |

(b) Rating

Table 4.3: Propensity Tables

but theoretically does not influence the choice of treatment and therefore cannot be interpreted as a confounder, we exclude this variable in our specifications.[2] The remaining pairs are correlations between covariates. In this case, each of these correlated features can be used as a predictor without favoring one over the others. To verify this, take for example the fourth pair, which displays a correlation of about 75% between euro- and U.S. dollar-denominated bonds. When splitting a tree, sometimes the Euro is used and sometimes the U.S. dollar, which leads to a distortion of their importance. Therefore, caution should be exercised when interpreting the results.

determines the number of variables that are considered as split candidates within a tree. Thus, with a higher number, the probability of selecting our highly correlated variable decreases. Similarly, one can enable the algorithm to tune a set of hyperparameters by cross-validation.

[2]For example, if a 1-year bond with a 4% coupon rate and a face value of 100 is sold for 100 (at par) in the market, the issue yield is also 4%. In case the issuer decides to grant a discount, the issue yield must be greater than the coupon rate. Vice versa, if the bond sells at a premium, issue yield < coupon rate.

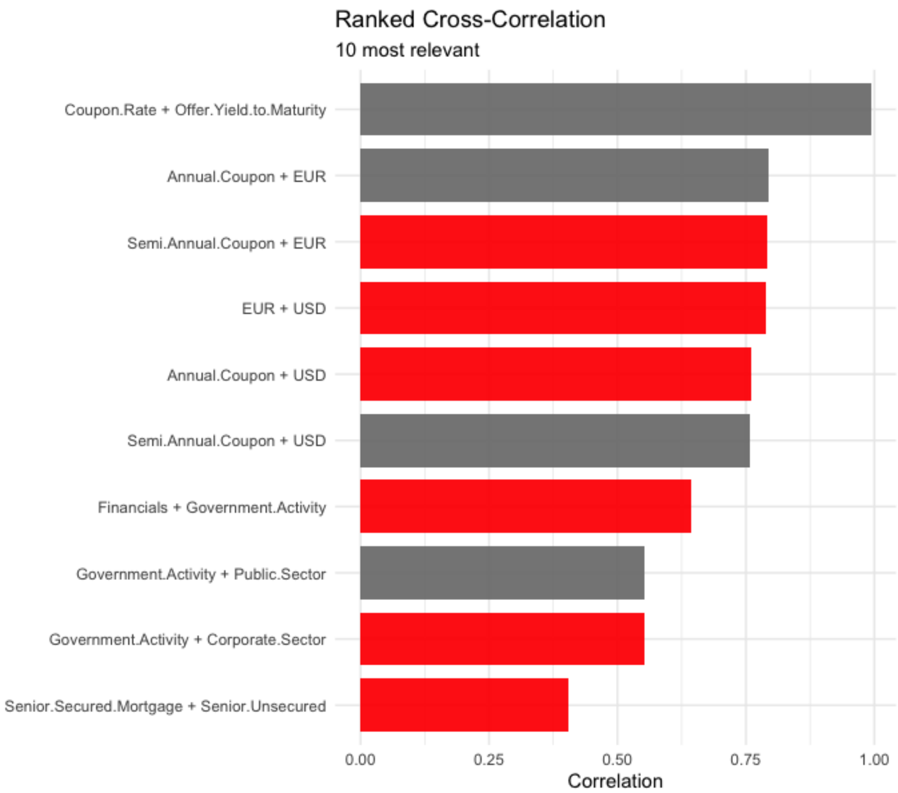



Figure 4.1: Ranked Cross-Correlation of 10 Most Relevant Pairs.

Note: Grey = Positive Correlation, Red = Negative Correlation.

## 4.3 Causal Forest Analysis

Our analysis consists of four data sets and three different methodological specifications. Based on these, we analyzed a total of 11 different models. To present them all in this paper is beyond the scope of readability and comprehensibility. Therefore, we select the two most relevant models to present in this chapter and report the results of the remaining models in the appendix. When deemed adequate, we refer the reader to the appendix.

Table 4.4 provides an overview of the ATE estimates for the 11 models. The first distinct observation we draw is that all of our models show a negative average treatment effect, supporting the greenium hypothesis. These estimates range from -0.186% to -1.032%, or, in financial jargon, from 18.6 to 103.2 basis points. The central tendency of this sample of ATEs is -0.43%. These results are of great significance not only in statistical terms, but also in economic terms. An important note is that the estimates of the models without issuer controls should only be interpreted for the sake of comparison with the methods which include issuer controls. Interestingly, we find that in all of our four data sets, the ATE estimate increases in magnitude when issuer controls are included. Furthermore, PSM Zerbib stands for Propensity Score Matching, which includes the variables proposed by ZERBIB [2017]. The matching is performed for each issuer cluster before the causal forest analysis. Therefore, we suggest that this method provides the best performance in terms of robustness.

Table 4.4: ATE across Models

| Dataset | Method | ATE Estimate | ATE Std. Err. |
|---|---|---|---|
| Data Universe | Without Issuer Controls | -0.3175919 | 0.02069961 |
| Data Universe | With Issuer Controls | -1.0322041 | 0.04456669 |
| Data Matched | Without Issuer Controls | -0.1857373 | 0.02581946 |
| Data Matched | With Issuer Controls | -0.5854021 | 0.02749895 |
| Data Matched | PSM Zerbib | -0.3431900 | 0.05963097 |
| USDEUR Matched | Without Issuer Controls | -0.1740170 | 0.02782810 |
| USDEUR Matched | With Issuer Controls | -0.5445872 | 0.02776807 |
| USDEUR Matched | PSM Zerbib | -0.2975631 | 0.05195736 |
| CBI Matched | Without Issuer Controls | -0.2558610 | 0.03095115 |
| CBI Matched | With Issuer Controls | -0.4943476 | 0.03200607 |
| CBI Matched | PSM Zerbib | -0.4999409 | 0.06891475 |

Figure 4.2 illustrates the ATE estimates and shows in dark green the two models we present in the following analysis. The reason we select them over the others is that the specifications of models (1) through (3) as well as (6) and (9) are less robust. Moreover, we can easily compare these two models with the models of the other two subsets.

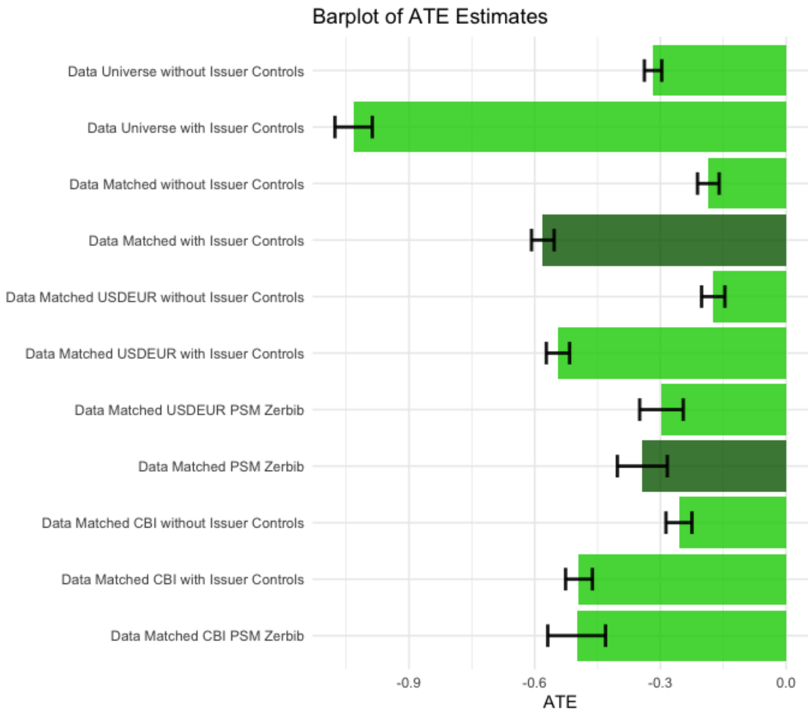



Figure 4.2: Barplot of ATE Estimates

### 4.3.1 Data Matched with Issuer Controls

#### Nuisance Parameter Check

First, we perform calibration checks to ensure that the nuisance parameters are well calibrated and that the propensity scores are sufficiently bounded from 0 and 1 and have adequate overlap. The latter checks the assumption of common support. The following calibration regressions are deployed to evaluate the performance of the propensity and outcome models:

$$W_i = \alpha \bar{e} + \beta \left( \hat{e}^{-i}(X_i) - \bar{e} \right) + \epsilon \quad \bar{e} := \frac{1}{n} \sum_{i=1}^{n} \hat{e}^{-i}(X_i) \quad \text{(Propensity Model)} \tag{4.1}$$

$$W_i = \alpha \bar{m} + \beta \left( \hat{m}^{-i}(X_i) - \bar{m} \right) + \epsilon \quad \bar{m} := \frac{1}{n} \sum_{i=1}^{n} \hat{m}^{-i}(X_i) \quad \text{(Outcome Model)} \tag{4.2}$$

The coefficients $\alpha$ and $\beta$ allow us to evaluate the performance of our estimates. If $\alpha = 1$, then the average prediction is correct. If $\beta = 1$, then the nuisance parameters adequately capture the underlying heterogeneity ATHEY ET AL. [2020]. First, the propensity score distribution is shown in Figure 4.3. The distributions do not overlap sufficiently, and the shape of the distributions also differs. Thus, we conclude that the assumption of common support is violated to some extent.

Second, the output of the calibration regressions is shown in Table 4.5. We conclude that both nuisance parameter estimations are correct in terms of average prediction and also seem to sufficiently capture the underlying heterogeneity.

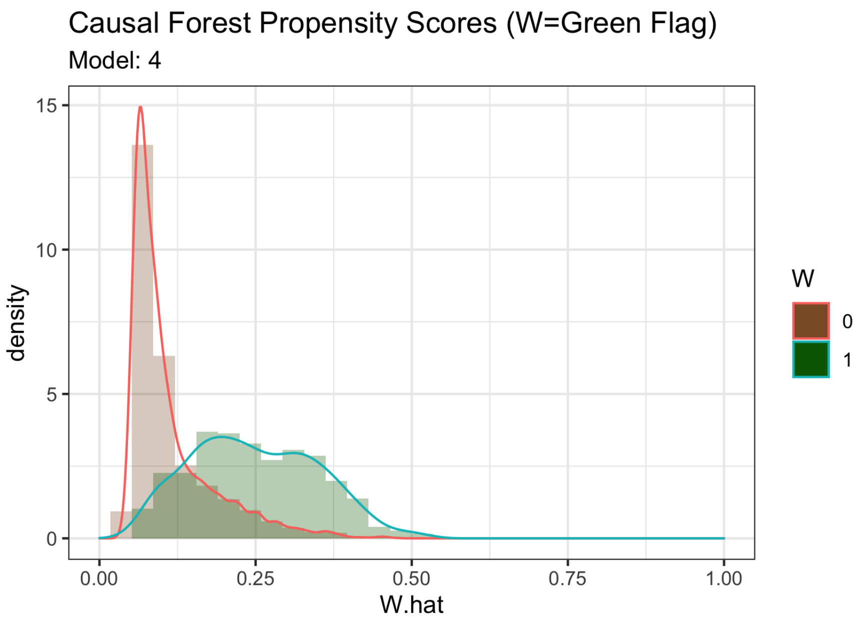



Figure 4.3: Propensity Score Distribution (Model 4)

| | Dependent variable: Green Flag |
|---|---|
| e.bar | 0.999*** |
| | (0.029) |
| e.residual | 2.076*** |
| | (0.062) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(a) Outcome Model

| | Dependent variable: Green Flag |
|---|---|
| m.bar | 1.000*** |
| | (0.011) |
| m.residual | 2.260*** |
| | (0.031) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(b) Propensity Model

Table 4.5: Calibration Regressions (Model 4)

### Heterogeneity Assessment

Another option to examine whether the trained causal forests have detected treatment heterogeneity is to "naively" examine the distribution of the individual CATE predictions. As can be seen in Figure 4.4, there is a clear trend, indicating that we do have heterogeneity indeed. Moreover, most of the observations lie between -0.75% and -0.25%.

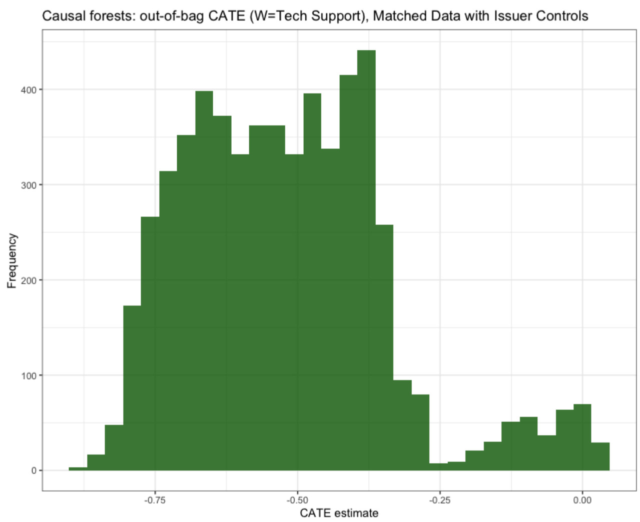



Figure 4.4: Distribution of CATE (Model 4)

The Generalized Random Forest (*grf*) package provides a measure of variable importance, indicating how frequently a variable appeared in a tree split. However, when estimating the importance of variables, a distortion occurs when both continuous and discrete variables are used. This is due to the fact that continuous variables contain a different amount of information than discrete variables. In particular, tree-based methods may be biased in favor of continuous variables due to the larger number of potential split points. This is especially a concern when the discrete variables are of the dummy type [O'Neill & Weeks, 2018, p. 3]. Besides, the issue of correlation applies here as well. Table 4.6 should therefore be considered only as a rough indication of the source of heterogeneity.

Table 4.6: Variable Importance (Model 4)

| Covariate | Value |
|---|---|
| 2022 | 0.1067 |
| Issue Amount | 0.0995 |
| Time to Maturity (Days) | 0.0876 |
| Annual Coupon | 0.0576 |
| Semi Annual Coupon | 0.056 |
| EUR | 0.0475 |

Another approach to synthesize the results of a complex algorithm, such as causal forests, is to form subgroups based on the magnitude of the predicted treatment effect. Compared to variable importance, this method is more descriptive and does not depend on whether a tree splits on a covariate or not. Therefore, it can provide us with valuable insight. With this approach, we divide the data into clusters, based on the n-tiles of the predicted treatment effect. In our case, we chose $n = 4$, which means that we look at the quartiles. Then we calculate the average treatment effect within each quartile by using two methods: Sample Average Treatment Effect and Augmented Inverse-Propensity Weighted (AIPW). The latter method is recommended for calculating the average treatment effect for observational data - as is the case in the present study [Athey et al., 2020]. Figure 4.5 shows the ATE point estimate with error bounds across four quartiles.

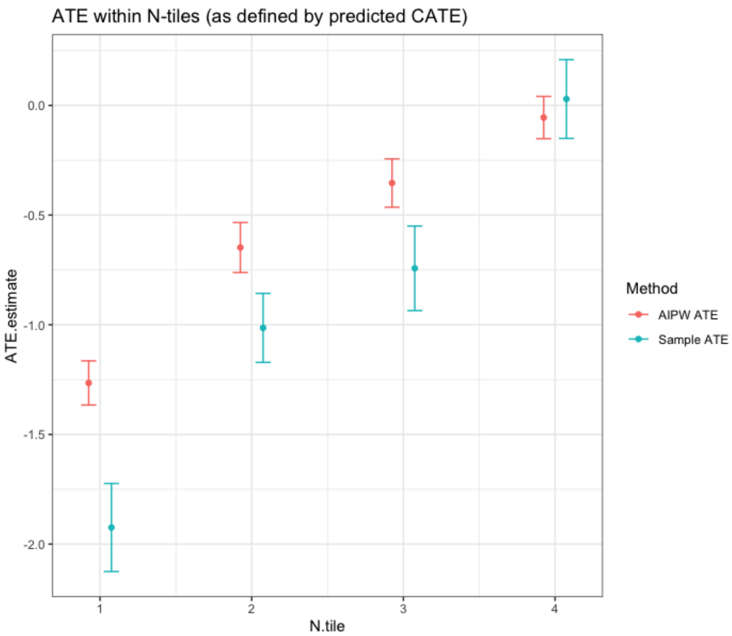
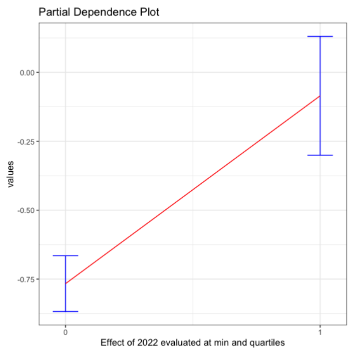


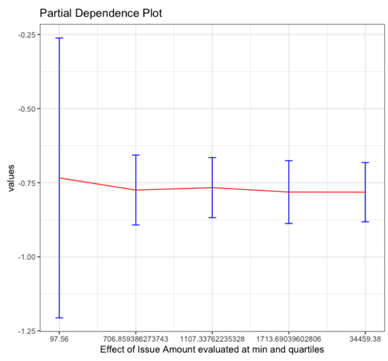

Figure 4.5: Graph of ATE within Subgroups (Model 4)

To confirm the hypothesis derived from the variable importance table and to assess which covariates influence these varying treatment effects across quantiles and to what extent, Table 4.7 presents the average level of each covariate across all quartiles. First, we observe that green bonds with a longer time to maturity fetch a lower average treatment effect (higher greenium) than shorter ones. Second, green bonds with an annual coupon have higher greenium, while green bonds with a semi-annual coupon have the lowest greenium. Third, green bond issuers from the financial sector tend to achieve lower greenium, while issuers from the technology and utilities sectors achieve the highest greenium. Fourth, euro-denominated green bonds have higher greenium, while U.S. dollar-denominated green bonds have the lowest greenium. And last but not least, green bonds issued from 2013 to 2016 experienced larger greeniums compared to green bonds issued between 2017 and 2022.

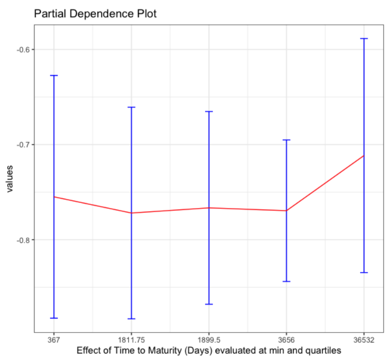
Another method to understand the rationale behind our causal forest black box predictions is to analyse partial dependency plots. Thereby we perform a ceteris paribus analysis on the three most important variables according to Table 4.6 by examining how the CATE estimates behave when we vary our variable of interest while keeping all other covariates fixed at their median. First, Figure 4.6a also shows that green bonds issued in 2022 have lower negative treatment effects compared to 2012. Second, the effect of issue amount remains stable. Thus, the isolated effect of issue amount on the treatment effect is approx. zero. However, the isolated effect of time of maturity in Figure 4.6c shows a slightly positive effect as already described above.




(a) Effect of 2022




(b) Effect of Issue Amount




(c) Effect of Time to Maturity (Days)

Figure 4.6: Partial Dependency Plots (Model 4)

Table 4.7: Heterogeneity across Covariates (Model 4)

| **Variable** | **Mean ntile1** | **Mean ntile2** | **Mean ntile3** | **Mean ntile4** |
|---|---|---|---|---|
| Time to Maturity (Days) | 2857.9 | 3539.32 | 2865.62 | 1801.99 |
| Issue Amount | 1704.89 | 1543.02 | 1400.54 | 1663.67 |
| Guarantor | 0.18 | 0.18 | 0.13 | 0.23 |
| 2013 | 0.11 | 0.05 | 0.06 | 0.05 |
| 2014 | 0.11 | 0.06 | 0.06 | 0.04 |
| 2015 | 0.05 | 0.09 | 0.09 | 0.07 |
| 2016 | 0.07 | 0.09 | 0.07 | 0.08 |
| 2017 | 0.02 | 0.1 | 0.1 | 0.07 |
| 2018 | 0 | 0.07 | 0.12 | 0.08 |
| 2019 | 0.04 | 0.13 | 0.12 | 0.03 |
| 2020 | 0.01 | 0.09 | 0.08 | 0.08 |
| 2021 | 0.04 | 0.09 | 0.09 | 0.06 |
| 2022 | 0 | 0 | 0 | 0.26 |
| Annual Coupon | 1 | 0.91 | 0.45 | 0.19 |
| Semi Annual Coupon | 0 | 0.09 | 0.54 | 0.8 |
| Quarterly | 0 | 0 | 0 | 0 |
| Senior Secured Mortgage | 0 | 0.15 | 0.13 | 0.05 |
| Senior Secured | 0.03 | 0.07 | 0.06 | 0.06 |
| Senior Unsecured | 0.82 | 0.62 | 0.46 | 0.73 |
| Senior Non Preferred | 0 | 0.01 | 0.09 | 0.02 |
| Senior Preferred | 0 | 0.03 | 0.12 | 0.05 |
| Senior Subordinated Unsecured | 0.01 | 0 | 0 | 0 |
| Subordinated Unsecured | 0.01 | 0.03 | 0.04 | 0 |
| Basic Materials | 0.01 | 0.01 | 0 | 0 |
| Consumer Cyclicals | 0.02 | 0 | 0 | 0 |
| Consumer Non Cyclicals | 0 | 0 | 0 | 0 |
| Energy | 0.02 | 0 | 0 | 0 |
| Financials | 0.54 | 0.61 | 0.7 | 0.8 |
| Healthcare | 0 | 0 | 0 | 0 |
| Industrials | 0.02 | 0.02 | 0.02 | 0.01 |
| Institutions, Associations & Organizations | 0.02 | 0.03 | 0.09 | 0.03 |
| Real Estate | 0 | 0 | 0 | 0 |
| Technology | 0.03 | 0 | 0 | 0 |
| Utilities | 0.05 | 0.01 | 0.01 | 0.01 |
| AAA | 0.31 | 0.5 | 0.44 | 0.5 |
| AA | 0.28 | 0.26 | 0.18 | 0.33 |
| A | 0.2 | 0.11 | 0.18 | 0.12 |
| BBB | 0.19 | 0.12 | 0.18 | 0.05 |
| BB | 0.02 | 0.01 | 0.02 | 0 |
| AUD | 0 | 0.01 | 0.03 | 0.01 |
| CAD | 0 | 0 | 0.02 | 0.01 |
| CLP | 0 | 0 | 0 | 0 |
| CNY | 0 | 0 | 0 | 0 |
| EUR | 0.95 | 0.68 | 0.36 | 0.17 |
| GBP | 0.03 | 0.11 | 0.07 | 0.02 |
| HKD | 0 | 0 | 0 | 0 |
| JPY | 0 | 0 | 0.04 | 0.04 |
| NZD | 0 | 0 | 0 | 0 |
| NOK | 0 | 0 | 0 | 0 |
| SEK | 0 | 0 | 0 | 0 |
| UYU | 0 | 0 | 0 | 0 |

Before proceeding to the second model, we provide the following comparative comments on the USDEUR and CBI subsets, which can be found in the appendix (7,7). First, the results for USDEUR show a very similar pattern, suggesting that our results are indeed mainly driven by these two markets without being influenced by other markets. Second, also the CBI subset is in line with our findings and even highlights the results more distinctively.

### 4.3.2 PSM Sample

#### Matching

The goal of matching is to achieve a balance between the treatment and comparison groups in terms of observable characteristics. We used the matching variables according to ZERBIB [2017], which are as follows: same issuer, currency, rating, seniority, collateral, and same time to maturity. A pitfall of this method is that we are loosing observations. Before matching, the number of observations in the treatment group amounted to 740 and in the control group to 4'988. After matching, the number of observations in both the treatment group and control group dropped to 698. It is crucial to assess the quality of matching. Therefore, we provide a summary table with different measures before and after matching. In particular, these measures include *standardized mean differences*, where a value close to zero indicates good balance, and *eCDF Max* (also called the Kolmogorov-Smirnov statistic), which provides an assessment of imbalance across the entire covariate distribution. We conclude that matching had a positive impact on the balance of covariates in our sample.

Table 4.8: Balance Check for Data Matched

| Variables | Std. Mean Diff. (Pre) | Std. Mean Diff. (Post) | eCDF Max (Pre) | eCDF Max (Post) |
|---|---|---|---|---|
| distance | 0.4557 | 0.3177 | 0.2716 | 0.1218 |
| MTG | -0.1013 | -0.0572 | 0.0247 | 0.0143 |
| SEC | -0.4107 | -0.1136 | 0.0151 | 0.0043 |
| SR | 0.1922 | 0.0095 | 0.0851 | 0.0043 |
| SRBN | 0.1214 | 0.1084 | 0.0281 | 0.0258 |
| SRP | 0.0821 | 0.0385 | 0.0208 | 0.0100 |
| SRSEC | -0.1176 | -0.0297 | 0.0221 | 0.0057 |
| SRSUB | -0.0287 | 0.0000 | 0.0011 | 0.0000 |
| SUB | -0.1647 | 0.0340 | 0.0135 | 0.0029 |
| UN | -0.3251 | -0.1043 | 0.0576 | 0.0186 |
| Time to Maturity (Days) | 0.0940 | 0.0814 | 0.1410 | 0.0688 |
| Guarantor | -0.1222 | 0.0000 | 0.0428 | 0.0000 |
| Australian Dollar | -0.1571 | 0.0000 | 0.0100 | 0.0000 |
| Canadian Dollar | 0.1344 | 0.0968 | 0.0213 | 0.0158 |
| Chilian Peso | 0.0259 | -0.0758 | 0.0010 | 0.0029 |
| Chinese Yuan Renminbi | 0.0313 | 0.0379 | 0.0012 | 0.0014 |
| Euro | 0.1842 | 0.0295 | 0.0895 | 0.0143 |
| Great Britain Pound | -0.1921 | -0.0528 | 0.0326 | 0.0086 |
| Hong Kong Dollar | 0.0313 | 0.0379 | 0.0012 | 0.0014 |
| Japanese Yen | -0.0296 | -0.0318 | 0.0039 | 0.0043 |
| Mexican Peso | -0.0152 | -0.0535 | 0.0002 | 0.0014 |
| New Zealand Dollar | 0.0366 | -0.0536 | 0.0019 | 0.0029 |
| Norwegian Krone | 0.0259 | 0.0000 | 0.0010 | 0.0000 |
| Swedish Krona | 0.1091 | 0.1016 | 0.0120 | 0.0115 |
| Swiss Franc | -0.0480 | -0.0535 | 0.0020 | 0.0014 |
| U.S. Dollar | -0.1781 | -0.0508 | 0.0803 | 0.0229 |
| Uruguayan Peso Uruguayano | 0.0259 | 0.0000 | 0.0010 | 0.0000 |
| A | 0.2103 | 0.0694 | 0.0881 | 0.0287 |
| AA | -0.1553 | -0.0736 | 0.0629 | 0.0301 |
| AAA | -0.2320 | -0.0573 | 0.1099 | 0.0272 |
| B | 0.0134 | 0.0536 | 0.0007 | 0.0029 |
| BB | 0.0030 | -0.0673 | 0.0003 | 0.0072 |
| BBB | 0.2052 | 0.0806 | 0.0837 | 0.0330 |

**Nuisance Parameter Check**

First, Figure 4.7 displays the propensity score model of our matched sample. In constrast to Figure 4.3, the propensity scores show more overlap. However, the distributions are not balanced. Thus, the common support assumption is also in this case somewhat violated. Since it is only the unbalanced distributions that cause issues, this should distort our results in terms of higher variance.

Second, the calibration regressions are shown in Table 4.9. The coefficients are all highly significant below the 1% threshold and approximately equal to one, indicating that, on the one hand, the average prediction is correct and, on the other hand, the nuisance parameters adequately capture the underlying heterogeneity.

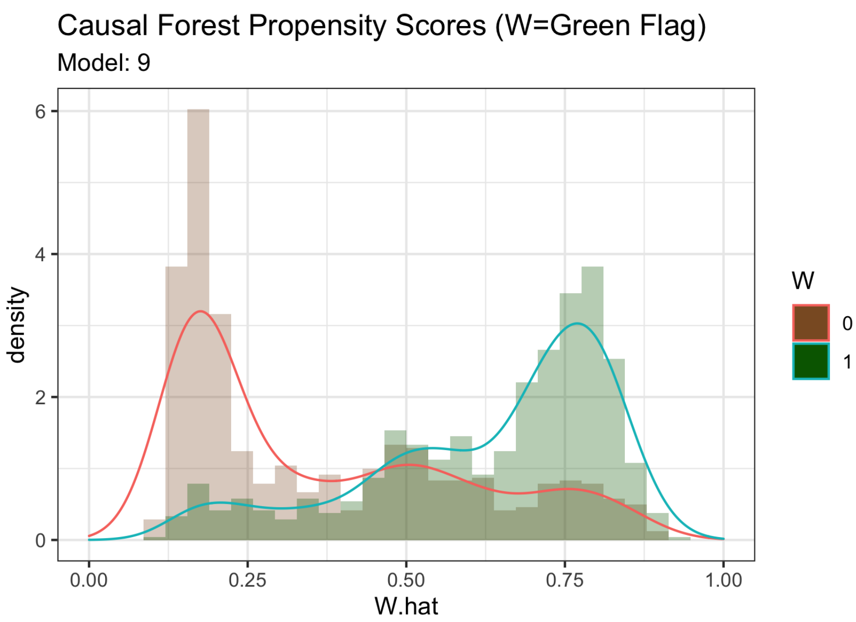



Figure 4.7: Propensity Score Distribution (Model 9)

| | *Dependent variable: Green Flag* |
|---|---|
| e.bar | $1.004^{***}$ |
| | (0.023) |
| e.residual | $1.092^{***}$ |
| | (0.041) |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

(a) Outcome Model

| | *Dependent variable: Green Flag* |
|---|---|
| m.bar | $1.004^{***}$ |
| | (0.015) |
| m.residual | $1.313^{***}$ |
| | (0.031) |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

(b) Propensity Model

Table 4.9: Calibration Regressions (Model 9)

### Heterogeneity Assessment

Again, we start by showing the distribution of CATEs in Figure 4.8. It can be noted that, compared to Figure 4.4, the distribution is more bell-formed with a central tendency around -0.3% and -0.2%.

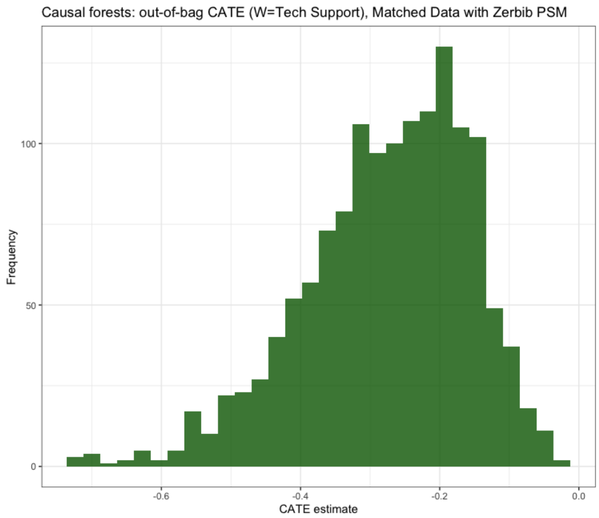



Figure 4.8: Distribution of CATE (Model 9)

The importance of the variables is shown in Table 4.10. Similar to table 4.6, the variables issue amount and time to maturity (days) are among the top 3 in importance.

Table 4.10: Variable Importance (Model 9)

| **Covariate** | **Value** |
|---|---|
| Issue Amount | 0.25640595 |
| Time to Maturity (Days) | 0.19958012 |
| 2020 | 0.08061582 |
| 2018 | 0.05449152 |
| Financials | 0.04008215 |
| 2022 | 0.03899863 |

Next, we show the mean ATE with error bound across quartiles in Figure 4.9. In contrast to Figure 4.5, the error bounds are larger and the overall range of the ATE is lower.

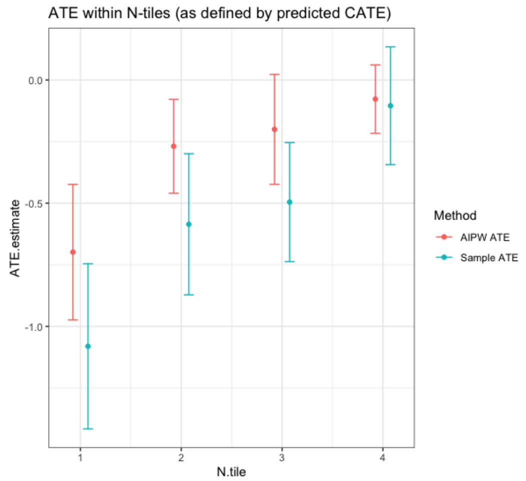
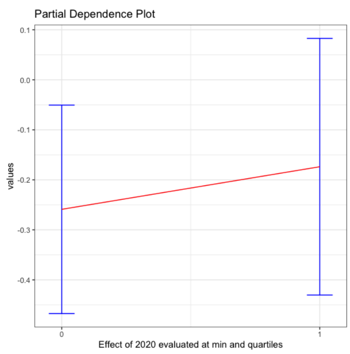


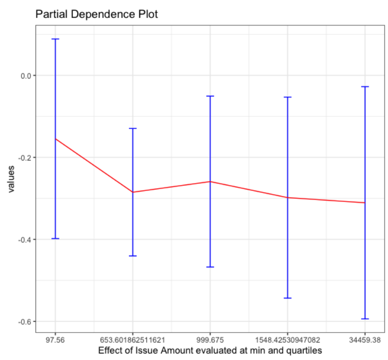

Figure 4.9: Graph of ATE within Quartiles (Model 9)

Also the heterogeneity across covariates shows a very similar pattern, compared to Table 4.7.

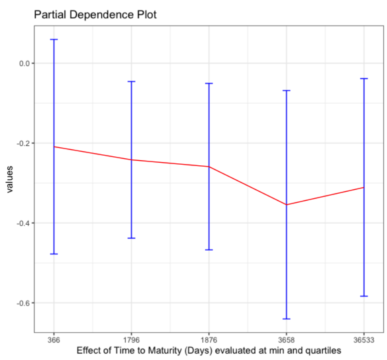
Next, the partial dependence plots are shown in Figure 4.10. Here we can observe the first differences. First, the slope of the effect of the 2022 dummy is now almost horizontal, suggesting that the isolated effect of green bonds from 2022 is less pronounced compared to 2012. Second, both the issue amount and the time to maturity have a negative effect, in contrast to our previous observations.




(a) Effect of 2022




(b) Effect of Issue Amount




(c) Effect of Time to Maturity (Days)

Figure 4.10: Partial Dependence Plots (Model 9)

Table 4.11: Heterogeneity across Covariates (Model 9)

| Variable | Mean ntile1 | Mean ntile2 | Mean ntile3 | Mean ntile4 |
|---|---|---|---|---|
| Time to Maturity (Days) | 2887.99 | 3733.21 | 2633.11 | 1810.53 |
| Issue Amount | 1694.43 | 1637.58 | 1248.52 | 1731.59 |
| Guarantor | 0.19 | 0.18 | 0.11 | 0.24 |
| 2013 | 0.11 | 0.05 | 0.05 | 0.06 |
| 2014 | 0.1 | 0.06 | 0.06 | 0.05 |
| 2015 | 0.06 | 0.09 | 0.09 | 0.06 |
| 2016 | 0.08 | 0.08 | 0.07 | 0.08 |
| 2017 | 0.02 | 0.11 | 0.1 | 0.07 |
| 2018 | 0 | 0.08 | 0.13 | 0.07 |
| 2019 | 0.03 | 0.13 | 0.11 | 0.04 |
| 2020 | 0.01 | 0.09 | 0.09 | 0.08 |
| 2021 | 0.05 | 0.09 | 0.09 | 0.04 |
| 2022 | 0 | 0 | 0 | 0.26 |
| Annual Coupon | 0.99 | 0.85 | 0.53 | 0.18 |
| Semi Annual Coupon | 0.01 | 0.15 | 0.47 | 0.82 |
| Quarterly | 0 | 0 | 0 | 0 |
| Senior Secured Mortgage | 0 | 0.18 | 0.11 | 0.05 |
| Senior Secured | 0.02 | 0.1 | 0.04 | 0.06 |
| Senior Unsecured | 0.87 | 0.53 | 0.49 | 0.75 |
| Senior Non Preferred | 0 | 0.02 | 0.09 | 0.02 |
| Senior Preferred | 0 | 0.03 | 0.14 | 0.04 |
| Senior Subordinated Unsecured | 0.01 | 0 | 0 | 0 |
| Subordinated Unsecured | 0.01 | 0.02 | 0.04 | 0 |
| Basic Materials | 0.01 | 0 | 0 | 0 |
| Consumer Cyclicals | 0.02 | 0 | 0 | 0 |
| Consumer Non Cyclicals | 0 | 0 | 0 | 0 |
| Energy | 0.02 | 0 | 0 | 0 |
| Financials | 0.52 | 0.61 | 0.72 | 0.8 |
| Healthcare | 0 | 0 | 0 | 0 |
| Industrials | 0.02 | 0.02 | 0.02 | 0 |
| Institutions, Associations & Organizations | 0.03 | 0.04 | 0.07 | 0.03 |
| Real Estate | 0 | 0 | 0 | 0 |
| Technology | 0.03 | 0 | 0 | 0 |
| Utilities | 0.04 | 0.01 | 0.01 | 0.01 |
| AAA | 0.31 | 0.51 | 0.37 | 0.55 |
| AA | 0.28 | 0.27 | 0.19 | 0.31 |
| A | 0.2 | 0.1 | 0.21 | 0.09 |
| BBB | 0.19 | 0.11 | 0.2 | 0.05 |
| BB | 0.02 | 0 | 0.02 | 0 |
| AUD | 0.01 | 0.04 | 0 | 0 |
| CAD | 0 | 0.02 | 0.01 | 0 |
| CLP | 0 | 0 | 0 | 0 |
| CNY | 0 | 0 | 0 | 0 |
| EUR | 0.93 | 0.74 | 0.32 | 0.16 |
| GBP | 0.06 | 0.13 | 0.03 | 0.01 |
| HKD | 0 | 0 | 0 | 0 |
| JPY | 0 | 0.03 | 0.05 | 0 |
| NZD | 0 | 0 | 0 | 0 |
| NOK | 0 | 0 | 0 | 0 |
| SEK | 0 | 0.01 | 0 | 0 |
| UYU | 0 | 0 | 0 | 0 |

Finally, both results of the USDEUR and CBI subsets show a very similar pattern to the one we described above.

## 4.4 Monte-Carlo Simulation

In a Monte Carlo simulation, the data used for the analysis is simulated. The baseline model of interest can be described as follows:

$$y = dy^1 + (1-d)y^0$$

### DGP 1

In the first DGP the model of interest can be described as follows:

$$\begin{aligned}
&y^0 \sim \text{CIR}^N \\
&y^1 = 0.1 + g(\mathbf{X}^{N\times K}) + \text{CIR}^N, \quad \text{where} \quad \mathbf{X}^{N\times K} \sim \mathcal{N}(0,1) \\
&g(\mathbf{X}^{N\times K}) = \mathbf{X'}^{N\times K}\beta \quad \text{where} \quad \beta = (1/K, ..., K/K) \\
&d \sim \mathcal{B}(p = 0.2)
\end{aligned}$$

where $\text{CIR}^N$ is a vector of interest rates generated by the Cox-Ingersoll-Ross (CIR) process. This process is used when calculating the evolution of interest rates. Mathematically, it has the following form [Cox et al., 1985, p. 391]:

$$dr_t = a(b - r_t)dt + \sigma\sqrt{r_t}dW_t \tag{4.3}$$

Here, $a$, $b$, and $\sigma$ are positive constants, $r_t$ is the interest rate, $t$ is the time, and $W_t$ denotes the standard Wiener process. Moreover, as can be seen from the first term, the process is mean-reverting, where $b$ is the long-run average interest rate, and $a$ is the speed of adjustment. Moreover, $\sigma$ is the volatility.

For this simple DGP all identifying assumptions are fulfilled such that we can estimate an unbiased ATE as $E[y_i^1 - y_i^0] = 0.1$.

### DGP 2

The second DGP is very similar to the first, with the exception that we allow the i.i.d assumption of the outcome to be violated. In order to do that we add an issuer dependency vector to the $\text{CIR}^N$ vector. The rationale being that bond returns are not generated in an i.i.d. process, but in a process that depends on the issuer. Therefore, we generate a random subset of issuers where each unique issuer receives a randomly assigned issuer effect. In this way, we are also able to adjust the intensity of the dependency.

### Results

The following histograms show the empirical distribution of our estimated ATE for both DGPs. Please note that we set $K$, the number of observable confounders to 10 and the number of observations to $N = 1'000$. The other parameters can be found in the code in the appendix.

First, Figure 4.11 shows the results for a relatively small issuer effect. We can note that the causal forest captures the ATE distribution very similarly for both DGPs. Thus, if the dependence effect is small, there is no cost to estimation performance.

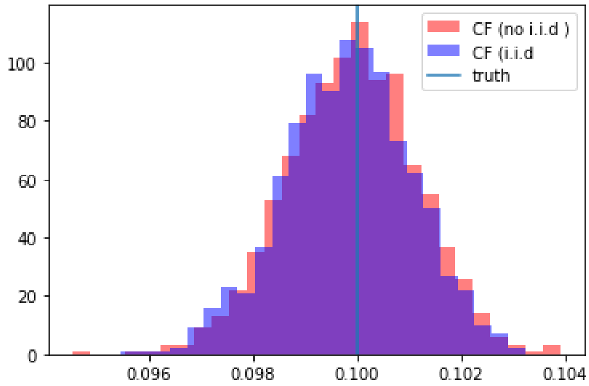



Figure 4.11: Low Issuer Effect

However, Figure 4.12 displays the results for a high issuer effect. In particular, this effect is five times higher as before. We can observe a difference in the distributions, namely that the ATE estimate of our DGP violating the i.i.d assumption has a higher variance compared to Figure 4.11. Thus, we conclude that violating the i.i.d. assumption only has a negative effect on the estimation accuracy of the causal forest. However, this negative effect is only marginal. Moreover, since we could argue that this dependence effect is relatively small in reality, the effect is approximately zero, as suggested by Figure 4.11.

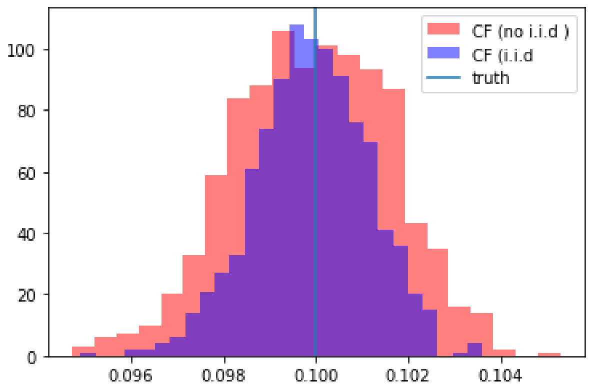



Figure 4.12: High Issuer Effect

CHAPTER 5

# DISCUSSION

## 5.1 Contribution to Existing Research

In this chapter, we discuss and compare the results of our thesis with the findings of the existing literature on greenium in the primary market. The second part of the section will discuss potential limitations of the present study, followed by a comment on possible future research directions.

We employed a total of 11 causal forests to measure the average treatment effect of a green bond on its yield at issuance. In addition, we also sought to uncover potential heterogeneities in the underlying treatment effects. All of our results support the greenium hypothesis. Specifically, the average treatment effect estimates range from -0.186% to -1.032%, or in financial jargon, from 18.6 to 103.2 basis points, with a central tendency of -0.43%. Therefore, this paper contributes to the literature by using a novel machine learning technique, i.e. causal forests, to estimate a statistically and economically significant greenium effect in the primary bond market. Moreover, to the best of our knowledge, our study is the first to estimate and uncover heterogeneity in treatment effects for green bonds. This heterogeneity is due to the following drivers: Green bonds that achieve a higher greenium tend to have a longer maturity, are issued with an annual coupon in the period 2013-2016, do not necessarily operate in the financial sector, and are predominantly issued in euros instead of U.S. dollars. Therefore, we complement the findings of (1) CARAMICHAEL & RAPP [2022] who concluded that the greenium is unevenly distributed and (2) GIANFRATE & PERI [2019]'s results which suggest that issuers operating mainly in the utilities and energy sector achieve a higher average advantage. In addition, our CBI subset analysis also complements previous evidence suggesting that the CBI certified green bonds fetch a higher premium [BAKER ET AL., 2018; FATICA ET AL., 2021]. Last but not least, our study provides evidence to the causal machine learning literature that the failure of the i.i.d assumption for the outcome variable has a negative effect on the accuracy of the causal forest average treatment effect estimate.

## 5.2 Limitations

Like in any study, the present thesis has its limitations. First, an important limitation of our study is that we do not adjust our outcome variable, i.e. the offer yield at issuance, for the risk-free interest rate. The reason for this is that, unfortunately, these data were not available to us on Eikon Refinitiv. As a consequence, our results may be biased upward. Second, also the for the other two rating agencies, i.e. S&P and Fitch, were not available. Thus, our rating bias is probably upward biased. Third, due to liquidity reasons, we restrict our sample to large bonds with an issue size of at least USD 500 million. Therefore, our study may lack external validity. Fourth, we only use the bond universe of the Eikon Refinitiv database, which does not cover the entire global universe and therefore exerts an additional negative impact on external validity.

## 5.3 Future Research

There are several fruitful avenues for future researchers. In our opinion, most effort should be directed to data collection. There may still be important covariates respectively confounders that are measured and available in databases. For example, a bond that is an index constituent may experience increased demand due to products derived from the index. Therefore, an index inclusion variable could provide further valuable insights. Other examples include measuring different shades of green or additional ESG flags. In particular, measuring the impact of the 2019 European Union Green Bond Taxonomy could be interesting. There are also three other types of sustainable bonds, namely social bonds, sustainability bonds and sustainability-linked bonds. According to expert opinions we obtained from the Swiss stock exchange SIX, especially the latter could make an important contribution to sustainable financing in the years to come.

CHAPTER 6

# CONCLUSION

The present thesis examined the greenium effect in the primary bond market by applying the causal forest method of the recent causal machine learning literature. It was shown that indeed a greenium is present with an estimated value between 18.6 to 103.2 basis points. The central tendency of our sample amounts to 43 basis points. These results are statistically and economically significant.

The process underlying our findings was as follows: We first attempted to provide a description of the green bond market and its peculiar phenomenon of the greenium. Thereafter, we conducted a thorough literature analysis in order to educate ourselves and the readers on the past research efforts which assessed the greenium in the primary market. Chapter three described the Eikon Refinitiv dataset, the variables which we extracted from it and the methodological approach. In particular, especially for robustness reasons, we divided our initial dataset in 3 subsets. Moreover, we used three different methodological specifications: (1) Estimation without issuer controls, (2) estimation with issuer controls and (3) additional propensity score matching before estimation. This approach provided us with a total of 11 models. In chapter four we verified the model assumptions as well as presented the descriptive statistics and causal forest results. For the sake of readability as well as comprehensibility, we have limited our presentation to the two most informative models, which also allows a simplified interpretation of the results based on the subsets. Besides finding negative average treatment effects throughout all of our models, we also aimed to detect possible heterogeneity. Indeed, we have found heterogeneity for which the following covariates play an substantial role with respect to the quartile with the highest greenium effect: (1) longer time to maturity, (2) issued during 2013 to 2016, (2) annual coupon, (3) not in the financial sector but rather in energy and utilities and (4) issued in euros. Another interesting result is that our CBI subset in combination with the propensity score matching method, which is our most rigorous model in terms of both the definition of "green" and the bond sample, has the highest greenium effect compared to the other subsets which used the

PSM approach. Therefore, this means that the additional certification costs are passed on to the investor, who bears a lower return on investment. Finally, due to the possible violation of the i.i.d assumption of our outcome variable, i.e. yield at issuance, we provided a Monte-Carlo simulation which computed the effects of such a violation on the accuracy of the average treatment effect estimate. Our results show that depending on the magnitude of the dependence, the effect is a less precise estimate due to an inflated variance. Nevertheless, the effect is relatively small for both small and large infringements. To conclude, our study ended with a discussion of the contributions and limitations, as well as recommendations for future research.

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APPENDIX A: UNIVERSE DATASET ANALYSIS

# A.1 Descriptive Statistics

## A.1.1 Summary Statistics

Table 1: Universe Green Bond Summary Statistics

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Time to Maturity (Days) | 1,024 | 3,214.172 | 2,417.984 | 367 | 1,834 | 3,660 | 21,922 |
| Issue Amount | 1,024 | 1,290.146 | 1,960.483 | 500 | 577.3 | 1,178.9 | 33,564 |
| Coupon Rate | 1,024 | 1.644 | 1.517 | 0 | 0.5 | 2.4 | 10 |
| Guarantor | 1,024 | 0.182 | 0.386 | 0 | 0 | 0 | 1 |
| Offer Yield to Maturity | 1,024 | 1.688 | 1.521 | −0 | 0.5 | 2.5 | 10 |
| 2008 | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2009 | 1,024 | 0.003 | 0.054 | 0 | 0 | 0 | 1 |
| 2010 | 1,024 | 0.005 | 0.070 | 0 | 0 | 0 | 1 |
| 2011 | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2012 | 1,024 | 0.007 | 0.082 | 0 | 0 | 0 | 1 |
| 2013 | 1,024 | 0.015 | 0.120 | 0 | 0 | 0 | 1 |
| 2014 | 1,024 | 0.011 | 0.103 | 0 | 0 | 0 | 1 |
| 2015 | 1,024 | 0.038 | 0.191 | 0 | 0 | 0 | 1 |
| 2016 | 1,024 | 0.043 | 0.203 | 0 | 0 | 0 | 1 |
| 2017 | 1,024 | 0.063 | 0.244 | 0 | 0 | 0 | 1 |
| 2018 | 1,024 | 0.074 | 0.262 | 0 | 0 | 0 | 1 |
| 2019 | 1,024 | 0.120 | 0.325 | 0 | 0 | 0 | 1 |
| 2020 | 1,024 | 0.164 | 0.371 | 0 | 0 | 0 | 1 |
| 2021 | 1,024 | 0.272 | 0.445 | 0 | 0 | 1 | 1 |
| 2022 | 1,024 | 0.185 | 0.388 | 0 | 0 | 0 | 1 |
| AAA | 1,024 | 0.248 | 0.432 | 0 | 0 | 0 | 1 |
| AA | 1,024 | 0.181 | 0.385 | 0 | 0 | 0 | 1 |
| A | 1,024 | 0.242 | 0.429 | 0 | 0 | 0 | 1 |
| BBB | 1,024 | 0.272 | 0.445 | 0 | 0 | 1 | 1 |
| BB | 1,024 | 0.042 | 0.201 | 0 | 0 | 0 | 1 |
| B | 1,024 | 0.014 | 0.116 | 0 | 0 | 0 | 1 |
| CCC | 1,024 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |
| Annual Coupon | 1,024 | 0.617 | 0.486 | 0 | 0 | 1 | 1 |
| Semi Annual Coupon | 1,024 | 0.380 | 0.486 | 0 | 0 | 1 | 1 |
| Quarterly | 1,024 | 0.002 | 0.044 | 0 | 0 | 0 | 1 |
| Monthly | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| Variable | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| Maturity | 1,024 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |

Table 2: Universe Green Bond Summary Statistics cont.

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Academic & Educational Services | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| Basic Materials | 1,024 | 0.021 | 0.142 | 0 | 0 | 0 | 1 |
| Consumer Cyclicals | 1,024 | 0.018 | 0.131 | 0 | 0 | 0 | 1 |
| Consumer Non-Cyclicals | 1,024 | 0.016 | 0.124 | 0 | 0 | 0 | 1 |
| Energy | 1,024 | 0.014 | 0.116 | 0 | 0 | 0 | 1 |
| Financials | 1,024 | 0.478 | 0.500 | 0 | 0 | 1 | 1 |
| Government Activity | 1,024 | 0.146 | 0.353 | 0 | 0 | 0 | 1 |
| Healthcare | 1,024 | 0.007 | 0.082 | 0 | 0 | 0 | 1 |
| Industrials | 1,024 | 0.057 | 0.231 | 0 | 0 | 0 | 1 |
| Institutions, Associations & Organizations | 1,024 | 0.064 | 0.246 | 0 | 0 | 0 | 1 |
| Real Estate | 1,024 | 0.035 | 0.184 | 0 | 0 | 0 | 1 |
| Technology | 1,024 | 0.021 | 0.145 | 0 | 0 | 0 | 1 |
| Utilities | 1,024 | 0.125 | 0.331 | 0 | 0 | 0 | 1 |
| AUD | 1,024 | 0.004 | 0.062 | 0 | 0 | 0 | 1 |
| BRL | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| CAD | 1,024 | 0.019 | 0.135 | 0 | 0 | 0 | 1 |
| CLP | 1,024 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |
| CNY | 1,024 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |
| COP | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| HRK | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| EUR | 1,024 | 0.568 | 0.496 | 0 | 0 | 1 | 1 |
| GBP | 1,024 | 0.028 | 0.166 | 0 | 0 | 0 | 1 |
| HKD | 1,024 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |
| JPY | 1,024 | 0.013 | 0.112 | 0 | 0 | 0 | 1 |
| KZT | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| MXN | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| NZD | 1,024 | 0.002 | 0.044 | 0 | 0 | 0 | 1 |
| NOK | 1,024 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |
| PEN | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| PHP | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| RUB | 1,024 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |
| SGD | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| SEK | 1,024 | 0.009 | 0.093 | 0 | 0 | 0 | 1 |
| CHF | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| THB | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| TRY | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| USD | 1,024 | 0.352 | 0.478 | 0 | 0 | 1 | 1 |
| UYU | 1,024 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |
| First-Lien Loan | 1,024 | 0.003 | 0.054 | 0 | 0 | 0 | 1 |
| First Mortgage | 1,024 | 0.015 | 0.120 | 0 | 0 | 0 | 1 |
| First Refunding Mortgage | 1,024 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |
| Second-Lien Loan | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| Junior Subordinated | 1,024 | 0.003 | 0.054 | 0 | 0 | 0 | 1 |
| Senior Secured Mortgage | 1,024 | 0.047 | 0.211 | 0 | 0 | 0 | 1 |
| Refunding Mortgage | 1,024 | 0.002 | 0.044 | 0 | 0 | 0 | 1 |
| Senior Secured | 1,024 | 0.045 | 0.207 | 0 | 0 | 0 | 1 |
| Senior Unsecured | 1,024 | 0.762 | 0.426 | 0 | 1 | 1 | 1 |
| Senior Non-Preferred | 1,024 | 0.041 | 0.198 | 0 | 0 | 0 | 1 |
| Senior Preferred | 1,024 | 0.049 | 0.216 | 0 | 0 | 0 | 1 |
| Senior Subordinated Unsecured | 1,024 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |
| Senior Subordinated Secured | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| Subordinated Unsecured | 1,024 | 0.005 | 0.070 | 0 | 0 | 0 | 1 |
| Subordinated Secured | 1,024 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| Unsecured | 1,024 | 0.024 | 0.154 | 0 | 0 | 0 | 1 |
| Public Sector | 1,024 | 0.361 | 0.481 | 0 | 0 | 1 | 1 |
| Corporate Sector | 1,024 | 0.639 | 0.481 | 0 | 0 | 1 | 1 |

Table 3: Universe Brown Bond Summary Statistics

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Time to Maturity (Days) | 11,179 | 2,680.561 | 2,347.479 | 366 | 1,712 | 3,656 | 36,533 |
| Issue Amount | 11,179 | 1,463 | 1,409 | 500 | 673 | 1,603 | 30,089 |
| Coupon Rate | 11,179 | 2.688 | 1.961 | 0 | 1.1 | 3.9 | 20 |
| Guarantor | 11,179 | 0.240 | 0.427 | 0 | 0 | 0 | 1 |
| Offer Yield to Maturity | 11,179 | 2.720 | 1.969 | 0 | 1.1 | 4.0 | 20 |
| 2008 | 11,179 | 0.059 | 0.235 | 0 | 0 | 0 | 1 |
| 2009 | 11,179 | 0.091 | 0.287 | 0 | 0 | 0 | 1 |
| 2010 | 11,179 | 0.084 | 0.277 | 0 | 0 | 0 | 1 |
| 2011 | 11,179 | 0.080 | 0.271 | 0 | 0 | 0 | 1 |
| 2012 | 11,179 | 0.093 | 0.291 | 0 | 0 | 0 | 1 |
| 2013 | 11,179 | 0.076 | 0.266 | 0 | 0 | 0 | 1 |
| 2014 | 11,179 | 0.076 | 0.265 | 0 | 0 | 0 | 1 |
| 2015 | 11,179 | 0.073 | 0.259 | 0 | 0 | 0 | 1 |
| 2016 | 11,179 | 0.068 | 0.252 | 0 | 0 | 0 | 1 |
| 2017 | 11,179 | 0.061 | 0.240 | 0 | 0 | 0 | 1 |
| 2018 | 11,179 | 0.056 | 0.230 | 0 | 0 | 0 | 1 |
| 2019 | 11,179 | 0.062 | 0.242 | 0 | 0 | 0 | 1 |
| 2020 | 11,179 | 0.047 | 0.211 | 0 | 0 | 0 | 1 |
| 2021 | 11,179 | 0.039 | 0.193 | 0 | 0 | 0 | 1 |
| 2022 | 11,179 | 0.035 | 0.183 | 0 | 0 | 0 | 1 |
| AAA | 11,179 | 0.364 | 0.481 | 0 | 0 | 1 | 1 |
| AA | 11,179 | 0.225 | 0.418 | 0 | 0 | 0 | 1 |
| A | 11,179 | 0.189 | 0.392 | 0 | 0 | 0 | 1 |
| BBB | 11,179 | 0.160 | 0.367 | 0 | 0 | 0 | 1 |
| BB | 11,179 | 0.038 | 0.191 | 0 | 0 | 0 | 1 |
| B | 11,179 | 0.021 | 0.142 | 0 | 0 | 0 | 1 |
| CCC | 11,179 | 0.003 | 0.050 | 0 | 0 | 0 | 1 |
| Annual Coupon | 11,179 | 0.583 | 0.493 | 0 | 0 | 1 | 1 |
| Semi Annual Coupon | 11,179 | 0.413 | 0.492 | 0 | 0 | 1 | 1 |
| Quarterly | 11,179 | 0.002 | 0.045 | 0 | 0 | 0 | 1 |
| Monthly | 11,179 | 0.0002 | 0.013 | 0 | 0 | 0 | 1 |
| Variable | 11,179 | 0.0001 | 0.009 | 0 | 0 | 0 | 1 |
| Maturity | 11,179 | 0.002 | 0.041 | 0 | 0 | 0 | 1 |
| Academic & Educational Services | 11,179 | 0.0001 | 0.009 | 0 | 0 | 0 | 1 |
| Basic Materials | 11,179 | 0.012 | 0.111 | 0 | 0 | 0 | 1 |
| Consumer Cyclicals | 11,179 | 0.017 | 0.130 | 0 | 0 | 0 | 1 |
| Consumer Non-Cyclicals | 11,179 | 0.014 | 0.115 | 0 | 0 | 0 | 1 |
| Energy | 11,179 | 0.013 | 0.111 | 0 | 0 | 0 | 1 |
| Financials | 11,179 | 0.689 | 0.463 | 0 | 0 | 1 | 1 |
| Government Activity | 11,179 | 0.170 | 0.376 | 0 | 0 | 0 | 1 |
| Healthcare | 11,179 | 0.003 | 0.052 | 0 | 0 | 0 | 1 |
| Industrials | 11,179 | 0.024 | 0.153 | 0 | 0 | 0 | 1 |
| Institutions, Associations & Organizations | 11,179 | 0.020 | 0.140 | 0 | 0 | 0 | 1 |
| Real Estate | 11,179 | 0.003 | 0.052 | 0 | 0 | 0 | 1 |
| Technology | 11,179 | 0.016 | 0.124 | 0 | 0 | 0 | 1 |
| Utilities | 11,179 | 0.020 | 0.139 | 0 | 0 | 0 | 1 |

Table 4: Universe Brown Bond Summary Statistics cont.

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| AUD | 11,179 | 0.009 | 0.096 | 0 | 0 | 0 | 1 |
| BRL | 11,179 | 0.0004 | 0.019 | 0 | 0 | 0 | 1 |
| CAD | 11,179 | 0.008 | 0.090 | 0 | 0 | 0 | 1 |
| CLP | 11,179 | 0.0002 | 0.013 | 0 | 0 | 0 | 1 |
| CNY | 11,179 | 0.0004 | 0.021 | 0 | 0 | 0 | 1 |
| COP | 11,179 | 0.0003 | 0.016 | 0 | 0 | 0 | 1 |
| HRK | 11,179 | 0.0001 | 0.009 | 0 | 0 | 0 | 1 |
| EUR | 11,179 | 0.485 | 0.500 | 0 | 0 | 1 | 1 |
| GBP | 11,179 | 0.054 | 0.227 | 0 | 0 | 0 | 1 |
| HKD | 11,179 | 0.0002 | 0.013 | 0 | 0 | 0 | 1 |
| JPY | 11,179 | 0.032 | 0.175 | 0 | 0 | 0 | 1 |
| KZT | 11,179 | 0.0001 | 0.009 | 0 | 0 | 0 | 1 |
| MXN | 11,179 | 0.001 | 0.034 | 0 | 0 | 0 | 1 |
| NZD | 11,179 | 0.001 | 0.025 | 0 | 0 | 0 | 1 |
| NOK | 11,179 | 0.0004 | 0.021 | 0 | 0 | 0 | 1 |
| PEN | 11,179 | 0.0004 | 0.019 | 0 | 0 | 0 | 1 |
| PHP | 11,179 | 0.0002 | 0.013 | 0 | 0 | 0 | 1 |
| RUB | 11,179 | 0.001 | 0.035 | 0 | 0 | 0 | 1 |
| SGD | 11,179 | 0.0003 | 0.016 | 0 | 0 | 0 | 1 |
| SEK | 11,179 | 0.0004 | 0.019 | 0 | 0 | 0 | 1 |
| CHF | 11,179 | 0.010 | 0.099 | 0 | 0 | 0 | 1 |
| THB | 11,179 | 0.0003 | 0.016 | 0 | 0 | 0 | 1 |
| TRY | 11,179 | 0.0002 | 0.013 | 0 | 0 | 0 | 1 |
| USD | 11,179 | 0.394 | 0.489 | 0 | 0 | 1 | 1 |
| UYU | 11,179 | 0.0003 | 0.016 | 0 | 0 | 0 | 1 |
| First-Lien Loan | 11,179 | 0.001 | 0.035 | 0 | 0 | 0 | 1 |
| First Mortgage | 11,179 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| First Refunding Mortgage | 11,179 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| Second-Lien Loan | 11,179 | 0.001 | 0.038 | 0 | 0 | 0 | 1 |
| Junior Subordinated | 11,179 | 0.0004 | 0.019 | 0 | 0 | 0 | 1 |
| Senior Secured Mortgage | 11,179 | 0.086 | 0.280 | 0 | 0 | 0 | 1 |
| Refunding Mortgage | 11,179 | 0.004 | 0.060 | 0 | 0 | 0 | 1 |
| Senior Secured | 11,179 | 0.077 | 0.267 | 0 | 0 | 0 | 1 |
| Senior Unsecured | 11,179 | 0.635 | 0.481 | 0 | 0 | 1 | 1 |
| Senior Non-Preferred | 11,179 | 0.014 | 0.118 | 0 | 0 | 0 | 1 |
| Senior Preferred | 11,179 | 0.029 | 0.168 | 0 | 0 | 0 | 1 |
| Senior Subordinated Unsecured | 11,179 | 0.005 | 0.067 | 0 | 0 | 0 | 1 |
| Senior Subordinated Secured | 11,179 | 0.0001 | 0.009 | 0 | 0 | 0 | 1 |
| Subordinated Unsecured | 11,179 | 0.020 | 0.140 | 0 | 0 | 0 | 1 |
| Subordinated Secured | 11,179 | 0.0001 | 0.009 | 0 | 0 | 0 | 1 |
| Unsecured | 11,179 | 0.109 | 0.312 | 0 | 0 | 0 | 1 |
| Public Sector | 11,179 | 0.382 | 0.486 | 0 | 0 | 1 | 1 |
| Corporate Sector | 11,179 | 0.618 | 0.486 | 0 | 0 | 1 | 1 |

### A.1.2 Raincloud Plots

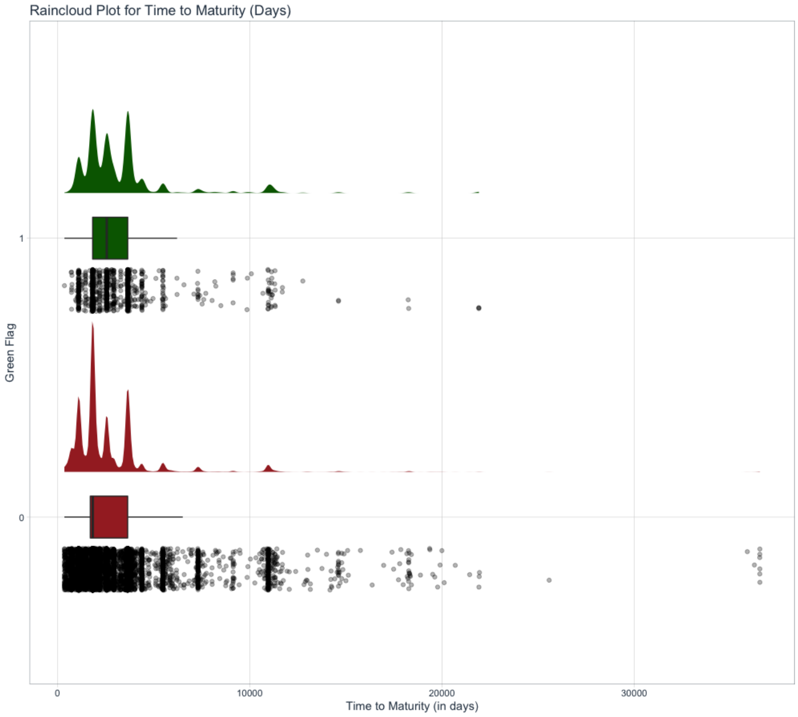



Figure 1: Raincloud Plot for Time to Maturity (Days)

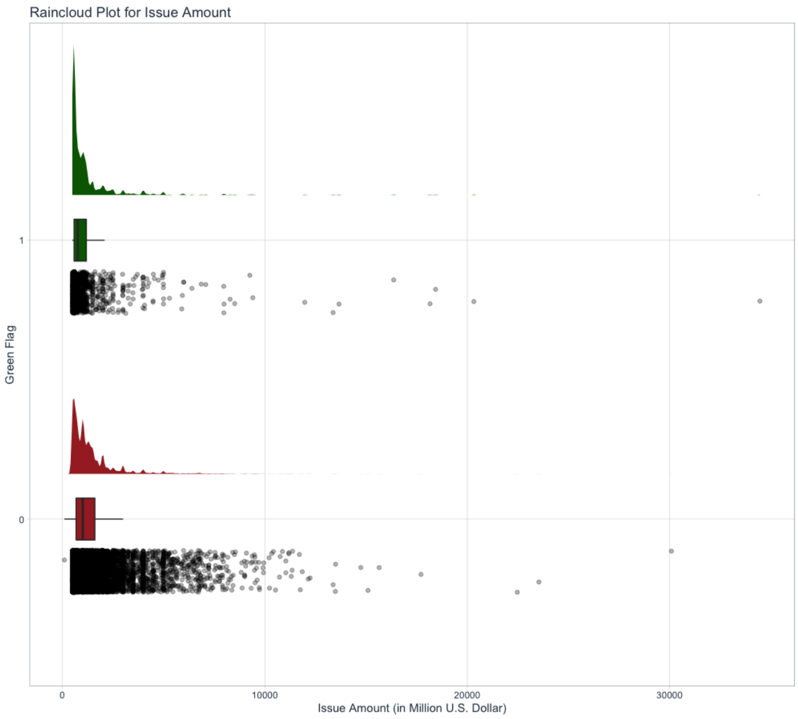



Figure 2: Raincloud for Issue Amount

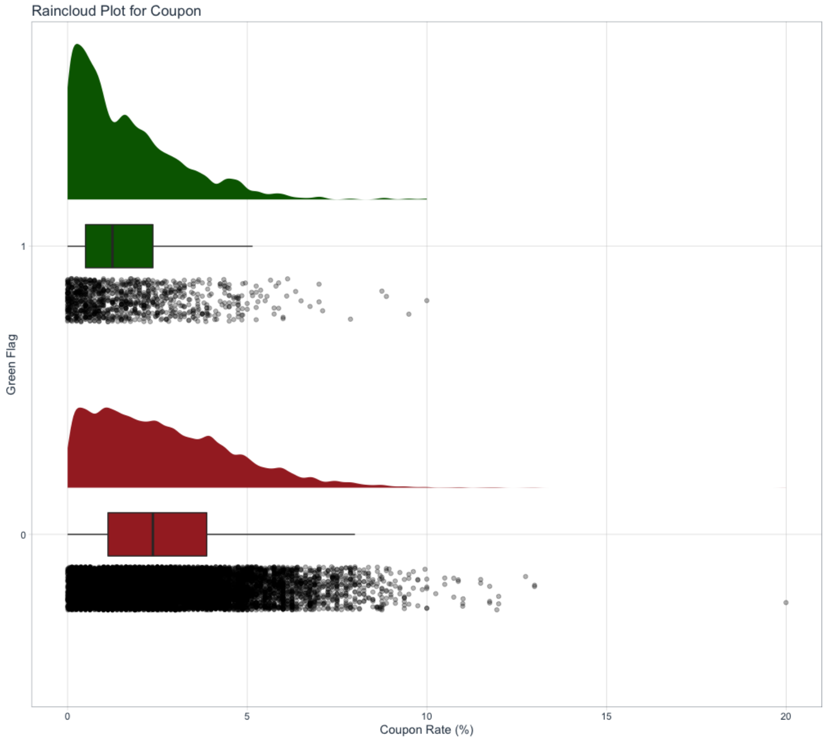



Figure 3: Raincloud for Coupon Rate

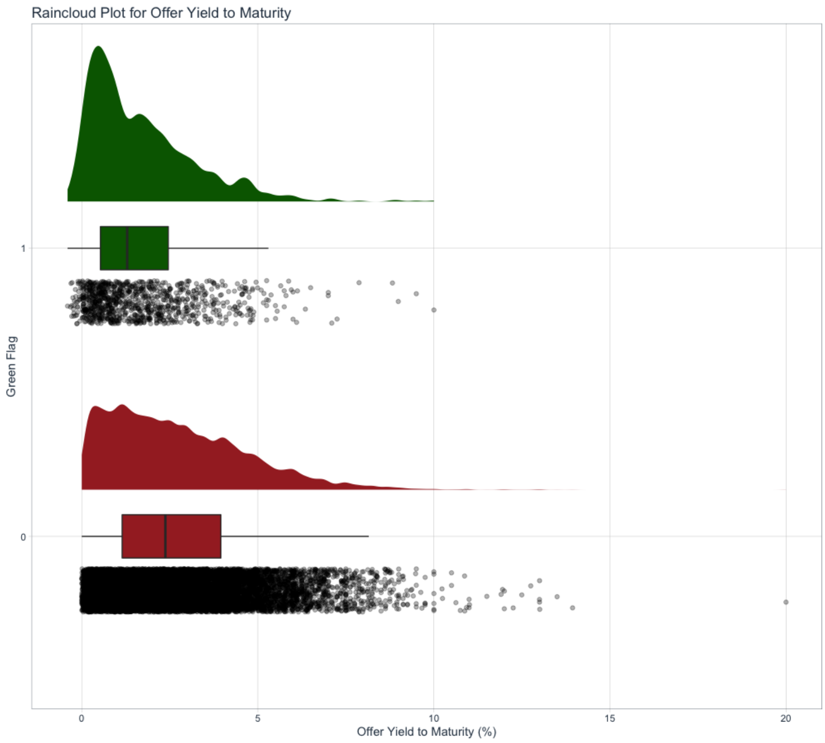



Figure 4: Raincloud for Issuance Yield

### A.1.3 Propensity Tables

Table 5: Propensity Table for Coupon Frequency

| Coupon Frequency | Green (%) | Brown (%) |
|---|---|---|
| Annual Coupon | 61.0 | 58.00 |
| Semi Annual Coupon | 38.7 | 41.60 |
| Quarterly | 0.2 | 0.20 |
| Monthly | 0.0 | 0.02 |
| Variable | 0.0 | 0.01 |
| Maturity | 0.1 | 0.02 |

Table 6: Propensity Table for Industry

| TRBC Industry | Green (%) | Brown (%) |
|---|---|---|
| Academic & Educational Services | 0.0 | 0.01 |
| Basic Materials | 2.2 | 1.20 |
| Consumer Cyclicals | 1.7 | 1.70 |
| Consumer Non-Cyclicals | 1.5 | 1.40 |
| Energy | 1.3 | 1.30 |
| Financials | 48.4 | 68.90 |
| Government Activity | 14.3 | 17.10 |
| Healthcare | 0.7 | 0.30 |
| Industrials | 5.7 | 2.40 |
| Institutions, Associations & Organizations | 6.4 | 2.00 |
| Real Estate | 3.4 | 0.30 |
| Technology | 2.1 | 1.60 |
| Utilities | 12.5 | 2.00 |

Table 7: Propensity Table for Currency

| Currency | Green (%) | Brown (%) | | Green (%) | Brown (%) |
|---|---|---|---|---|---|
| Currency | Green | Brown | | Green | Brown |
| AUD | 0.4 | 0.90 | NZD | 0.2 | 0.10 |
| BRL | 0.0 | 0.04 | NOK | 0.1 | 0.04 |
| CAD | 2.0 | 0.90 | PEN | 0.0 | 0.04 |
| CLP | 0.1 | 0.02 | PHP | 0.0 | 0.02 |
| CNY | 0.1 | 0.04 | RUB | 0.1 | 0.10 |
| COP | 0.0 | 0.03 | SGD | 0.0 | 0.03 |
| HRK | 0.0 | 0.01 | SEK | 0.9 | 0.04 |
| EUR | 56.0 | 48.20 | CHF | 0.0 | 1.00 |
| GBP | 2.9 | 5.40 | THB | 0.0 | 0.03 |
| HKD | 0.1 | 0.02 | TRY | 0.0 | 0.02 |
| JPY | 1.2 | 3.10 | USD | 35.9 | 39.90 |
| KZT | 0.0 | 0.01 | UYU | 0.1 | 0.03 |
| MXN | 0.0 | 0.10 | | | |

Table 8: Propensity Table for Seniority

| **Seniority** | **Green (%)** | **Brown (%)** |
|---|---|---|
| First-Lien Loan | 0.3 | 0.10 |
| First Mortgage | 1.4 | 0.00 |
| First Refunding Mortgage | 0.1 | 0.00 |
| Second-Lien Loan | 0.0 | 0.10 |
| Junior Subordinated | 0.3 | 0.04 |
| Senior Secured Mortgage | 4.5 | 8.40 |
| Refunding Mortgage | 0.2 | 0.40 |
| Senior Secured | 4.3 | 7.60 |
| Senior Unsecured | 72.3 | 62.20 |
| Senior Non-Preferred | 3.9 | 1.40 |
| Senior Preferred | 4.7 | 2.80 |
| Senior Subordinated Unsecured | 0.1 | 0.50 |
| Senior Subordinated Secured | 0.0 | 0.01 |
| Subordinated Unsecured | 0.5 | 2.00 |
| Subordinated Secured | 0.0 | 0.01 |
| Unsecured | 2.3 | 10.80 |

| **Issuer Sector** | **Green (%)** | **Brown (%)** |
|---|---|---|
| Public Sector | 36.2 | 38.2 |
| Corporate Sector | 63.8 | 61.8 |

(a) Issuer Sector

| **Guarantor** | **Green (%)** | **Brown (%)** |
|---|---|---|
| Guarantor | 18.4 | 24 |
| No Guarantor | 81.6 | 76 |

(b) Guarantor

Table 9: Propensity Table for Issuer Sector and Guarantor

## A.2 Causal Forest

### A.2.1 Without Issuer Controls

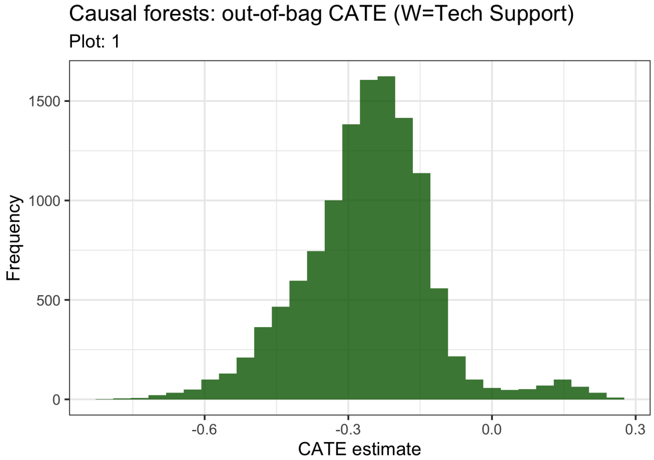



Figure 5: Distribution of CATE (Model 1)

#### A.2.1.1 Nuisance Parameter Check

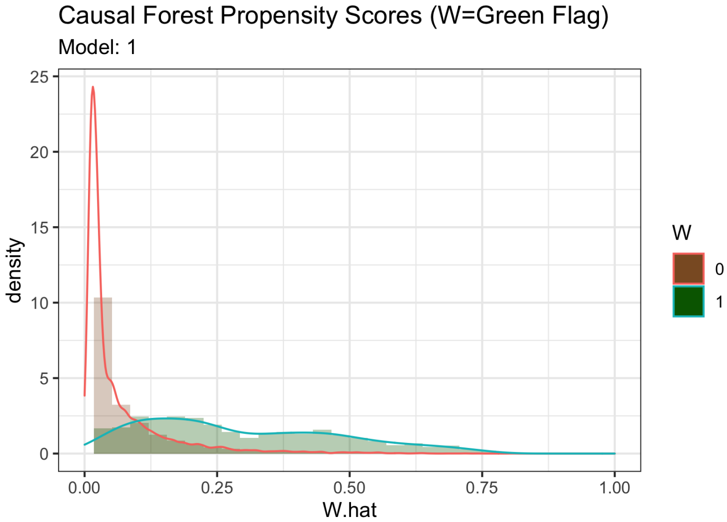



Figure 6: Propensity Score Distribution (Model 1)

| | *Dependent variable: Green Flag* |
|---|---|
| e.bar | 1.008*** |
| | (0.025) |
| e.residual | 1.254*** |
| | (0.032) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(a) Outcome Model

| | *Dependent variable: Green Flag* |
|---|---|
| m.bar | 0.999*** |
| | (0.003) |
| m.residual | 1.173*** |
| | (0.008) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(b) Propensity Model

Table 10: Calibration Regressions (Model 1)

#### A.2.1.2 Heterogeneity Assessment

Table 11: Variable Importance (Model 1)

| **Covariate** | **Value** |
|---|---|
| 2022 | 0.18699691 |
| Issue Amount | 0.15014007 |
| Utilities | 0.11702269 |
| Time to Maturity (Days) | 0.11682995 |
| BBB | 0.05125039 |
| Financials | 0.04937156 |

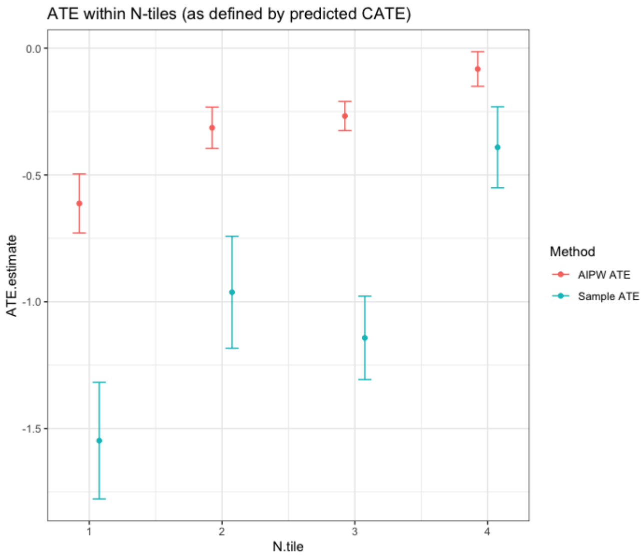
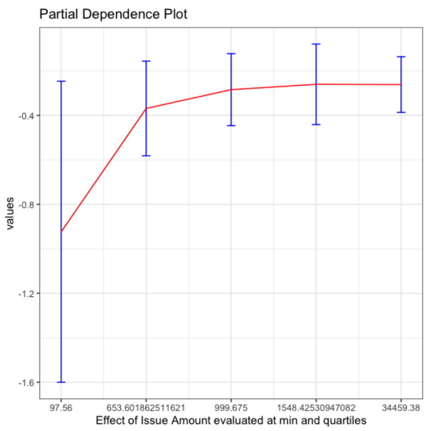
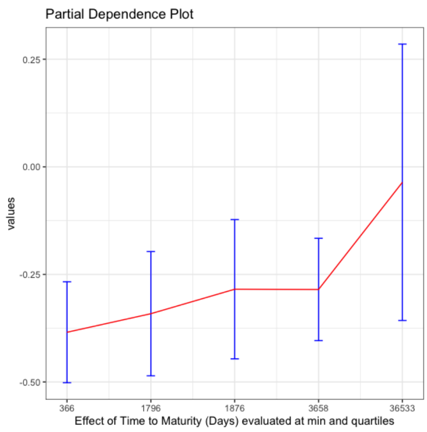


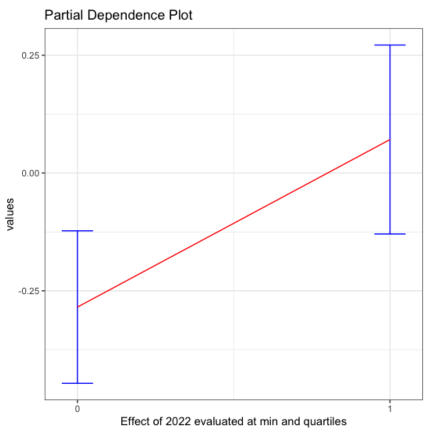

Figure 7: Graph of ATE within Subgroups (Model 1)




(a) Effect of Issue Amount




(b) Effect of Time to Maturity (Days)




(c) Effect of 2022

Figure 8: Partial Dependence Plots (Model 1)

Table 12: Heterogeneity across Covariates (Model 1)

| Variable | Mean ntile1 | Mean ntile2 | Mean ntile3 | Mean ntile4 |
|---|---|---|---|---|
| Time to Maturity (Days) | 2882.61 | 2628.35 | 2585.12 | 2805.31 |
| Issue Amount | 974.29 | 1274.77 | 1618.74 | 1916.95 |
| Guarantor | 0.25 | 0.22 | 0.21 | 0.27 |
| 2013 | 0.11 | 0.07 | 0.07 | 0.04 |
| 2014 | 0.09 | 0.08 | 0.06 | 0.05 |
| 2015 | 0.07 | 0.08 | 0.07 | 0.06 |
| 2016 | 0.07 | 0.08 | 0.06 | 0.05 |
| 2017 | 0.06 | 0.08 | 0.07 | 0.04 |
| 2018 | 0.02 | 0.03 | 0.09 | 0.09 |
| 2019 | 0.06 | 0.11 | 0.08 | 0.02 |
| 2020 | 0.02 | 0.02 | 0.05 | 0.14 |
| 2021 | 0.03 | 0.05 | 0.09 | 0.07 |
| 2022 | 0 | 0.01 | 0.01 | 0.17 |
| Annual Coupon | 0.51 | 0.7 | 0.67 | 0.48 |
| Semi Annual Coupon | 0.49 | 0.3 | 0.33 | 0.52 |
| Quarterly | 0 | 0 | 0 | 0 |
| Monthly | 0 | 0 | 0 | 0 |
| Variable | 0 | 0 | 0 | 0 |
| First Lien Loan | 0 | 0 | 0 | 0 |
| First Mortgage | 0 | 0 | 0 | 0 |
| First Refunding Mortgage | 0 | 0 | 0 | 0 |
| Second Lien Loan | 0 | 0 | 0 | 0 |
| Junior Subordinated | 0 | 0 | 0 | 0 |
| Senior Secured Mortgage | 0 | 0.11 | 0.13 | 0.09 |
| Refunding Mortgage | 0 | 0 | 0.01 | 0 |
| Senior Secured | 0.02 | 0.07 | 0.1 | 0.12 |
| Senior Unsecured | 0.87 | 0.66 | 0.54 | 0.52 |
| Senior Non Preferred | 0 | 0.01 | 0.02 | 0.04 |
| Senior Preferred | 0 | 0.01 | 0.05 | 0.06 |
| Senior Subordinated Unsecured | 0.01 | 0 | 0.01 | 0 |
| Senior Subordinated Secured | 0 | 0 | 0 | 0 |
| Subordinated Unsecured | 0.03 | 0.02 | 0.02 | 0.01 |
| Subordinated Secured | 0 | 0 | 0 | 0 |
| Academic & Educational Services | 0 | 0 | 0 | 0 |
| Basic Materials | 0.04 | 0.01 | 0 | 0 |
| Consumer Cyclicals | 0.04 | 0.02 | 0.01 | 0 |
| Consumer Non Cyclicals | 0.04 | 0.01 | 0.01 | 0 |
| Energy | 0.04 | 0.01 | 0 | 0 |
| Financials | 0.45 | 0.65 | 0.74 | 0.84 |
| Healthcare | 0.01 | 0 | 0 | 0 |
| Industrials | 0.06 | 0.03 | 0.01 | 0.01 |
| Institutions, Associations & Organizations | 0 | 0.02 | 0.05 | 0.03 |
| Real Estate | 0.01 | 0.01 | 0 | 0 |
| Technology | 0.05 | 0.01 | 0.01 | 0 |
| Utilities | 0.11 | 0 | 0 | 0 |
| AAA | 0.07 | 0.32 | 0.5 | 0.52 |
| AA | 0.07 | 0.23 | 0.27 | 0.31 |
| A | 0.31 | 0.26 | 0.13 | 0.08 |
| BBB | 0.42 | 0.12 | 0.07 | 0.07 |
| BB | 0.08 | 0.05 | 0.02 | 0.01 |
| B | 0.05 | 0.02 | 0.01 | 0 |

Table 13: Heterogeneity across Covariates cont. (Model 1)

| Variable | Mean ntile1 | Mean ntile2 | Mean ntile3 | Mean ntile4 |
|---|---|---|---|---|
| AUD | 0 | 0.01 | 0.01 | 0.01 |
| BRL | 0 | 0 | 0 | 0 |
| EUR | 0.42 | 0.61 | 0.56 | 0.38 |
| GBP | 0.05 | 0.03 | 0.05 | 0.08 |
| HKD | 0 | 0 | 0 | 0 |
| JPY | 0.02 | 0.04 | 0.04 | 0.02 |
| KZT | 0 | 0 | 0 | 0 |
| MXN | 0 | 0 | 0 | 0 |
| NZD | 0 | 0 | 0 | 0 |
| NOK | 0 | 0 | 0 | 0 |
| PEN | 0 | 0 | 0 | 0 |
| PHP | 0 | 0 | 0 | 0 |
| RUB | 0 | 0 | 0 | 0 |
| SGD | 0 | 0 | 0 | 0 |
| SEK | 0 | 0 | 0 | 0 |
| CHF | 0.01 | 0.01 | 0.01 | 0.01 |
| THB | 0 | 0 | 0 | 0 |
| TRY | 0 | 0 | 0 | 0 |
| UYU | 0 | 0 | 0 | 0 |

### A.2.2 With Issuer Controls

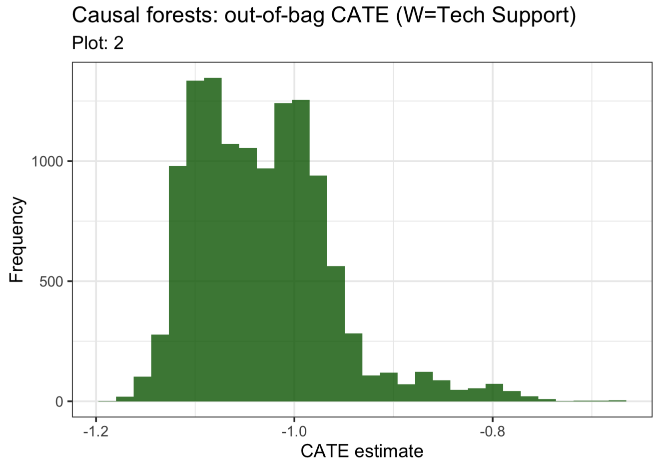



Figure 9: Distribution of CATE (Model 2)

#### A.2.2.1 Nuisance Parameter Check

| | *Dependent variable: Green Flag* |
|---|---|
| e.bar | 1.000*** |
| | (0.027) |
| e.residual | 17.468*** |
| | (0.525) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(a) Outcome Model

| | *Dependent variable: Green Flag* |
|---|---|
| m.bar | 1.000*** |
| | (0.006) |
| m.residual | 12.864*** |
| | (0.161) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(b) Propensity Model

Table 14: Calibration Regressions (Model 2)

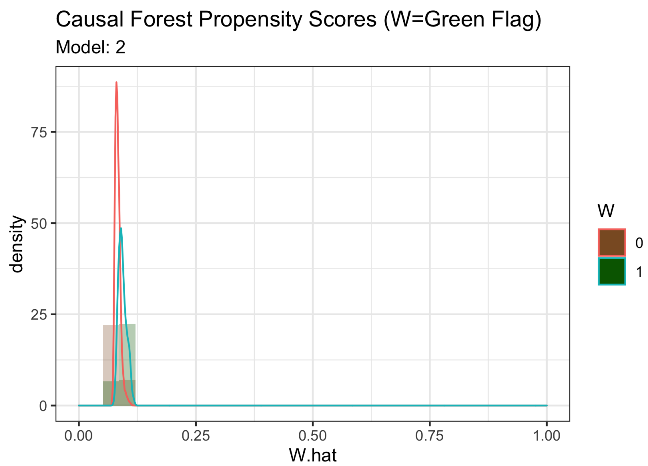



Figure 10: Propensity Score Distribution (Model 2)

#### A.2.2.2 Heterogeneity Assessment

Table 15: Variable Importance (Model 2)

| Covariate | Value |
|---|---|
| 2022 | 0.06224698 |
| Issue Amount | 0.05900688 |
| Time to Maturity (Days) | 0.05695576 |
| Utilities | 0.05664093 |
| Annual Coupon | 0.05452951 |
| Semi Annual Coupon | 0.05223546 |

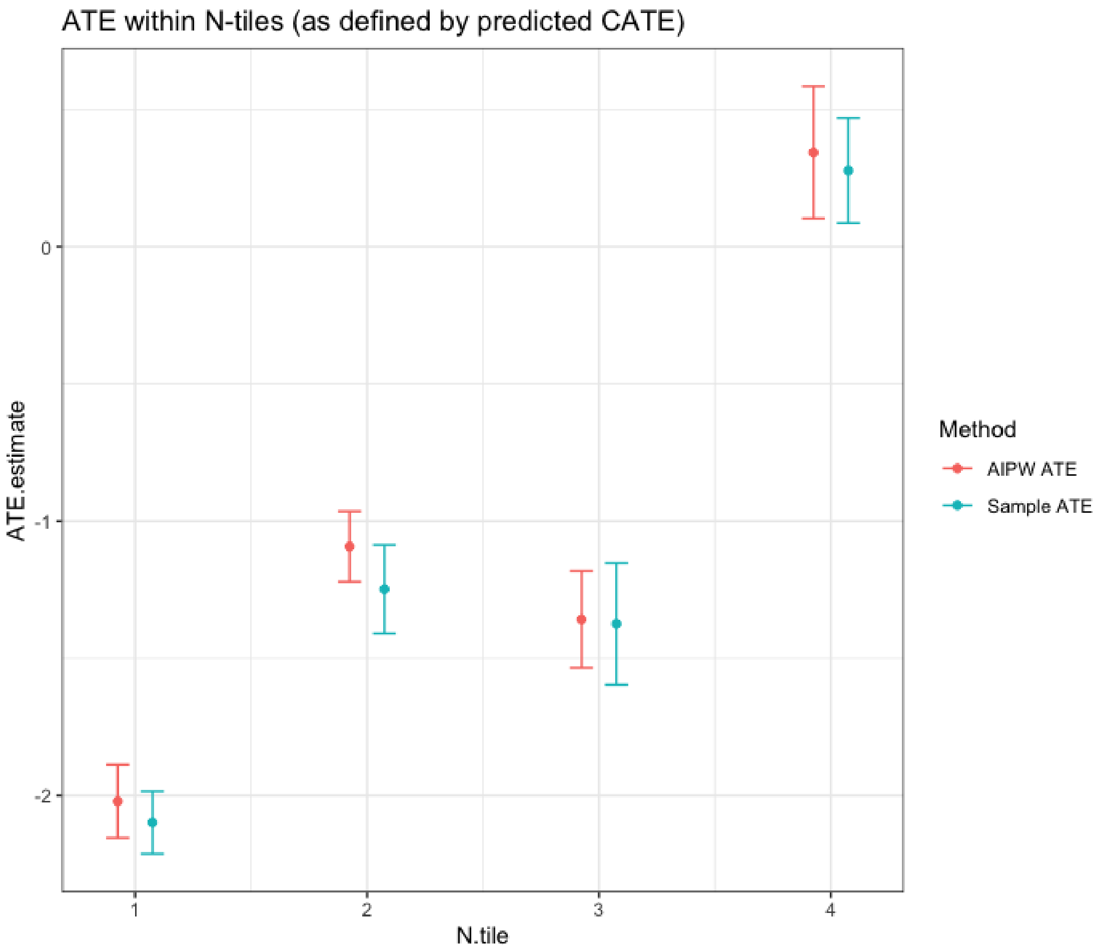
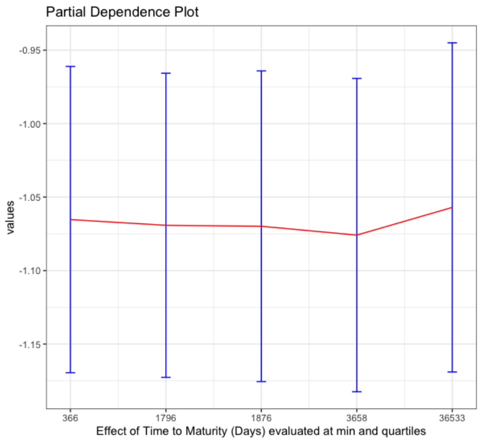
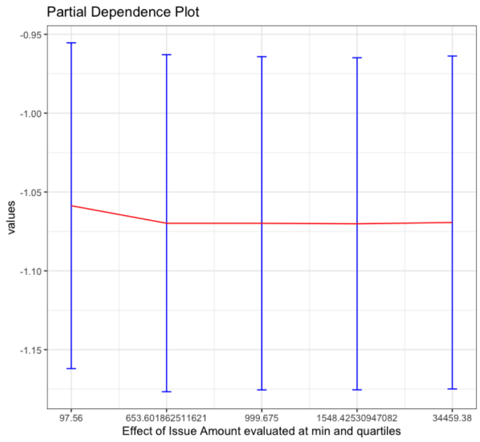


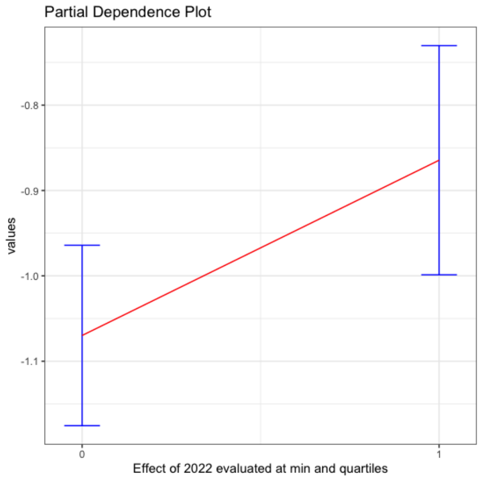

Figure 11: Graph of ATE within Subgroups (Model 2)




(a) Effect of Time to Maturity (Days)




(b) Effect of Issue Amount




(c) Effect of 2022

Figure 12: Partial Dependency Plots (Model 2)

Table 16: Heterogeneity across Covariates (Model 2)

| Variable | Mean ntile1 | Mean ntile2 | Mean ntile3 | Mean ntile4 |
|---|---|---|---|---|
| Time to Maturity (Days) | 3054.57 | 2681.13 | 2724.35 | 2441.21 |
| Issue Amount | 1554.38 | 1410.58 | 1278.26 | 1541.41 |
| Guarantor | 0.22 | 0.26 | 0.2 | 0.25 |
| 2013 | 0.1 | 0.05 | 0.08 | 0.05 |
| 2014 | 0.09 | 0.06 | 0.07 | 0.05 |
| 2015 | 0.06 | 0.09 | 0.07 | 0.06 |
| 2016 | 0.05 | 0.07 | 0.07 | 0.08 |
| 2017 | 0.04 | 0.07 | 0.07 | 0.06 |
| 2018 | 0.01 | 0.08 | 0.06 | 0.08 |
| 2019 | 0.05 | 0.08 | 0.07 | 0.06 |
| 2020 | 0.07 | 0.04 | 0.08 | 0.03 |
| 2021 | 0.1 | 0.04 | 0.07 | 0.03 |
| 2022 | 0 | 0 | 0 | 0.19 |
| Annual Coupon | 1 | 0.97 | 0.23 | 0.14 |
| Semi Annual Coupon | 0 | 0.02 | 0.76 | 0.85 |
| Quarterly | 0 | 0 | 0 | 0 |
| Monthly | 0 | 0 | 0 | 0 |
| Variable | 0 | 0 | 0 | 0 |
| First Lien Loan | 0 | 0 | 0 | 0 |
| First Mortgage | 0 | 0 | 0 | 0 |
| First Refunding Mortgage | 0 | 0 | 0 | 0 |
| Second Lien Loan | 0 | 0 | 0 | 0 |
| Junior Subordinated | 0 | 0 | 0 | 0 |
| Senior Secured Mortgage | 0.01 | 0.19 | 0.08 | 0.05 |
| Refunding Mortgage | 0 | 0 | 0 | 0.01 |
| Senior Secured | 0.01 | 0.12 | 0.06 | 0.11 |
| Senior Unsecured | 0.87 | 0.45 | 0.75 | 0.51 |
| Senior Non Preferred | 0.03 | 0.03 | 0 | 0.01 |
| Senior Preferred | 0.03 | 0.06 | 0.01 | 0.03 |
| Senior Subordinated Unsecured | 0.01 | 0 | 0.01 | 0 |
| Senior Subordinated Secured | 0 | 0 | 0 | 0 |
| Subordinated Unsecured | 0.02 | 0.01 | 0.03 | 0.02 |
| Subordinated Secured | 0 | 0 | 0 | 0 |
| Academic & Educational Services | 0 | 0 | 0 | 0 |
| Basic Materials | 0.02 | 0 | 0.01 | 0.01 |
| Consumer Cyclicals | 0.03 | 0.02 | 0.02 | 0.01 |
| Consumer Non Cyclicals | 0.02 | 0.01 | 0.02 | 0.01 |
| Energy | 0.02 | 0 | 0.02 | 0.01 |
| Financials | 0.57 | 0.77 | 0.67 | 0.68 |
| Healthcare | 0 | 0 | 0 | 0 |
| Industrials | 0.06 | 0.01 | 0.02 | 0.02 |
| Institutions, Associations & Organizations | 0.03 | 0.01 | 0.04 | 0.01 |
| Real Estate | 0.01 | 0 | 0.01 | 0 |
| Technology | 0.03 | 0 | 0.01 | 0.01 |
| Utilities | 0 | 0 | 0.04 | 0.07 |
| AAA | 0.1 | 0.56 | 0.26 | 0.5 |
| AA | 0.26 | 0.23 | 0.15 | 0.25 |
| A | 0.31 | 0.09 | 0.26 | 0.11 |
| BBB | 0.28 | 0.09 | 0.24 | 0.08 |
| BB | 0.03 | 0.02 | 0.05 | 0.05 |
| B | 0.01 | 0.01 | 0.04 | 0.02 |

Table 17: Heterogeneity across Covariates cont. (Model 2)

| Variable | Mean ntile1 | Mean ntile2 | Mean ntile3 | Mean ntile4 |
|---|---|---|---|---|
| AUD | 0 | 0 | 0.01 | 0.02 |
| BRL | 0 | 0 | 0 | 0 |
| CAD | 0 | 0 | 0.01 | 0.03 |
| CLP | 0 | 0 | 0 | 0 |
| CNY | 0 | 0 | 0 | 0 |
| COP | 0 | 0 | 0 | 0 |
| HRK | 0 | 0 | 0 | 0 |
| EUR | 0.94 | 0.74 | 0.16 | 0.12 |
| GBP | 0.03 | 0.1 | 0.04 | 0.04 |
| HKD | 0 | 0 | 0 | 0 |
| JPY | 0 | 0 | 0.02 | 0.09 |
| KZT | 0 | 0 | 0 | 0 |
| MXN | 0 | 0 | 0 | 0 |
| NZD | 0 | 0 | 0 | 0 |
| NOK | 0 | 0 | 0 | 0 |
| PEN | 0 | 0 | 0 | 0 |
| PHP | 0 | 0 | 0 | 0 |
| RUB | 0 | 0 | 0 | 0 |
| SGD | 0 | 0 | 0 | 0 |
| SEK | 0 | 0 | 0 | 0 |
| CHF | 0 | 0.01 | 0.02 | 0 |
| THB | 0 | 0 | 0 | 0 |
| TRY | 0 | 0 | 0 | 0 |
| UYU | 0 | 0 | 0 | 0 |

# Appendix B: Issuer matched Dataset Analysis

## B.1 Descriptive Statistics

### B.1.1 Summary Statistics

Table 18: Data Matched Green Bond Summary Statistics

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Time to Maturity (Days) | 740 | 2,921.549 | 1,897.858 | 367 | 1,833 | 3,659 | 18,269 |
| Issue Amount | 740 | 1,383.033 | 2,127.100 | 500.000 | 578.613 | 1,219.467 | 33,563.640 |
| Coupon Rate | 740 | 1.265 | 1.196 | 0.000 | 0.375 | 1.875 | 9.500 |
| Guarantor | 740 | 0.143 | 0.351 | 0 | 0 | 0 | 1 |
| Offer Yield to Maturity | 740 | 1.301 | 1.204 | −0.403 | 0.420 | 1.906 | 9.500 |
| Green Flag | 740 | 1.000 | 0.000 | 1 | 1 | 1 | 1 |
| 2008 | 740 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2009 | 740 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2010 | 740 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2011 | 740 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2012 | 740 | 0.001 | 0.037 | 0 | 0 | 0 | 1 |
| 2013 | 740 | 0.011 | 0.103 | 0 | 0 | 0 | 1 |
| 2014 | 740 | 0.012 | 0.110 | 0 | 0 | 0 | 1 |
| 2015 | 740 | 0.036 | 0.188 | 0 | 0 | 0 | 1 |
| 2016 | 740 | 0.046 | 0.210 | 0 | 0 | 0 | 1 |
| 2017 | 740 | 0.073 | 0.260 | 0 | 0 | 0 | 1 |
| 2018 | 740 | 0.085 | 0.279 | 0 | 0 | 0 | 1 |
| 2019 | 740 | 0.127 | 0.333 | 0 | 0 | 0 | 1 |
| 2020 | 740 | 0.170 | 0.376 | 0 | 0 | 0 | 1 |
| 2021 | 740 | 0.247 | 0.432 | 0 | 0 | 0 | 1 |
| 2022 | 740 | 0.191 | 0.393 | 0 | 0 | 0 | 1 |
| AAA | 740 | 0.341 | 0.474 | 0 | 0 | 1 | 1 |
| AA | 740 | 0.207 | 0.405 | 0 | 0 | 0 | 1 |
| A | 740 | 0.227 | 0.419 | 0 | 0 | 0 | 1 |
| BBB | 740 | 0.211 | 0.408 | 0 | 0 | 0 | 1 |
| BB | 740 | 0.012 | 0.110 | 0 | 0 | 0 | 1 |
| B | 740 | 0.003 | 0.052 | 0 | 0 | 0 | 1 |
| Annual Coupon | 740 | 0.682 | 0.466 | 0 | 0 | 1 | 1 |
| Semi Annual Coupon | 740 | 0.316 | 0.465 | 0 | 0 | 1 | 1 |
| Quarterly | 740 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| Maturity | 740 | 0.001 | 0.037 | 0 | 0 | 0 | 1 |
| Basic Materials | 740 | 0.014 | 0.116 | 0 | 0 | 0 | 1 |
| Consumer Cyclicals | 740 | 0.008 | 0.090 | 0 | 0 | 0 | 1 |
| Consumer Non-Cyclicals | 740 | 0.008 | 0.090 | 0 | 0 | 0 | 1 |

Table 19: Data Matched Green Bond Summary Statistics cont.

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Energy | 740 | 0.003 | 0.052 | 0 | 0 | 0 | 1 |
| Financials | 740 | 0.569 | 0.496 | 0 | 0 | 1 | 1 |
| Government Activity | 740 | 0.195 | 0.396 | 0 | 0 | 0 | 1 |
| Healthcare | 740 | 0.003 | 0.052 | 0 | 0 | 0 | 1 |
| Industrials | 740 | 0.045 | 0.207 | 0 | 0 | 0 | 1 |
| Institutions, Associations & Organizations | 740 | 0.084 | 0.277 | 0 | 0 | 0 | 1 |
| Real Estate | 740 | 0.018 | 0.131 | 0 | 0 | 0 | 1 |
| Technology | 740 | 0.009 | 0.097 | 0 | 0 | 0 | 1 |
| Utilities | 740 | 0.046 | 0.210 | 0 | 0 | 0 | 1 |
| AUD | 740 | 0.004 | 0.064 | 0 | 0 | 0 | 1 |
| CAD | 740 | 0.026 | 0.158 | 0 | 0 | 0 | 1 |
| CLP | 740 | 0.001 | 0.037 | 0 | 0 | 0 | 1 |
| CNY | 740 | 0.001 | 0.037 | 0 | 0 | 0 | 1 |
| EUR | 740 | 0.618 | 0.486 | 0 | 0 | 1 | 1 |
| GBP | 740 | 0.030 | 0.170 | 0 | 0 | 0 | 1 |
| HKD | 740 | 0.001 | 0.037 | 0 | 0 | 0 | 1 |
| JPY | 740 | 0.018 | 0.131 | 0 | 0 | 0 | 1 |
| NZD | 740 | 0.003 | 0.052 | 0 | 0 | 0 | 1 |
| NOK | 740 | 0.001 | 0.037 | 0 | 0 | 0 | 1 |
| SEK | 740 | 0.012 | 0.110 | 0 | 0 | 0 | 1 |
| USD | 740 | 0.284 | 0.451 | 0 | 0 | 1 | 1 |
| UYU | 740 | 0.001 | 0.037 | 0 | 0 | 0 | 1 |
| Senior Secured Mortgage | 740 | 0.064 | 0.244 | 0 | 0 | 0 | 1 |
| Senior Secured | 740 | 0.036 | 0.188 | 0 | 0 | 0 | 1 |
| Senior Unsecured | 740 | 0.732 | 0.443 | 0 | 0 | 1 | 1 |
| Senior Non-Preferred | 740 | 0.057 | 0.232 | 0 | 0 | 0 | 1 |
| Senior Preferred | 740 | 0.069 | 0.253 | 0 | 0 | 0 | 1 |
| Senior Subordinated Unsecured | 740 | 0.001 | 0.037 | 0 | 0 | 0 | 1 |
| Subordinated Unsecured | 740 | 0.007 | 0.082 | 0 | 0 | 0 | 1 |
| Unsecured | 740 | 0.032 | 0.177 | 0 | 0 | 0 | 1 |
| Public Sector | 740 | 0.482 | 0.500 | 0 | 0 | 1 | 1 |
| Corporate Sector | 740 | 0.518 | 0.500 | 0 | 0 | 1 | 1 |

Table 20: Data Matched Brown Bond Summary Statistics

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Time to Maturity (Days) | 4,988 | 2,743.163 | 2,594.663 | 373 | 1,744.8 | 3,630.2 | 36,532 |
| Issue Amount | 4,988 | 1,610.370 | 1,534.290 | 500.000 | 750.000 | 1,750.000 | 30,089.370 |
| Coupon Rate | 4,988 | 2.160 | 1.618 | 0.001 | 0.875 | 3.125 | 20.000 |
| Guarantor | 4,988 | 0.186 | 0.389 | 0 | 0 | 0 | 1 |
| Offer Yield to Maturity | 4,988 | 2.189 | 1.623 | 0.001 | 0.940 | 3.126 | 20.000 |
| Green Flag | 4,988 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2008 | 4,988 | 0.046 | 0.210 | 0 | 0 | 0 | 1 |
| 2009 | 4,988 | 0.057 | 0.231 | 0 | 0 | 0 | 1 |
| 2010 | 4,988 | 0.069 | 0.254 | 0 | 0 | 0 | 1 |
| 2011 | 4,988 | 0.074 | 0.261 | 0 | 0 | 0 | 1 |
| 2012 | 4,988 | 0.090 | 0.287 | 0 | 0 | 0 | 1 |
| 2013 | 4,988 | 0.075 | 0.263 | 0 | 0 | 0 | 1 |
| 2014 | 4,988 | 0.076 | 0.265 | 0 | 0 | 0 | 1 |

Table 21: Data Matched Brown Bond Summary Statistics cont.

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| 2015 | 4,988 | 0.081 | 0.273 | 0 | 0 | 0 | 1 |
| 2016 | 4,988 | 0.082 | 0.275 | 0 | 0 | 0 | 1 |
| 2017 | 4,988 | 0.071 | 0.257 | 0 | 0 | 0 | 1 |
| 2018 | 4,988 | 0.068 | 0.251 | 0 | 0 | 0 | 1 |
| 2019 | 4,988 | 0.073 | 0.260 | 0 | 0 | 0 | 1 |
| 2020 | 4,988 | 0.051 | 0.219 | 0 | 0 | 0 | 1 |
| 2021 | 4,988 | 0.042 | 0.200 | 0 | 0 | 0 | 1 |
| 2022 | 4,988 | 0.046 | 0.209 | 0 | 0 | 0 | 1 |
| AAA | 4,988 | 0.450 | 0.498 | 0 | 0 | 1 | 1 |
| AA | 4,988 | 0.270 | 0.444 | 0 | 0 | 1 | 1 |
| A | 4,988 | 0.139 | 0.346 | 0 | 0 | 0 | 1 |
| BBB | 4,988 | 0.127 | 0.333 | 0 | 0 | 0 | 1 |
| BB | 4,988 | 0.012 | 0.108 | 0 | 0 | 0 | 1 |
| B | 4,988 | 0.002 | 0.045 | 0 | 0 | 0 | 1 |
| Annual Coupon | 4,988 | 0.631 | 0.483 | 0 | 0 | 1 | 1 |
| Semi Annual Coupon | 4,988 | 0.366 | 0.482 | 0 | 0 | 1 | 1 |
| Quarterly | 4,988 | 0.002 | 0.047 | 0 | 0 | 0 | 1 |
| Maturity | 4,988 | 0.001 | 0.028 | 0 | 0 | 0 | 1 |
| Basic Materials | 4,988 | 0.005 | 0.071 | 0 | 0 | 0 | 1 |
| Consumer Cyclicals | 4,988 | 0.006 | 0.077 | 0 | 0 | 0 | 1 |
| Consumer Non-Cyclicals | 4,988 | 0.002 | 0.049 | 0 | 0 | 0 | 1 |
| Energy | 4,988 | 0.005 | 0.072 | 0 | 0 | 0 | 1 |
| Financials | 4,988 | 0.675 | 0.469 | 0 | 0 | 1 | 1 |
| Government Activity | 4,988 | 0.233 | 0.423 | 0 | 0 | 0 | 1 |
| Healthcare | 4,988 | 0.001 | 0.028 | 0 | 0 | 0 | 1 |
| Industrials | 4,988 | 0.011 | 0.106 | 0 | 0 | 0 | 1 |
| Institutions, Associations & Organizations | 4,988 | 0.038 | 0.192 | 0 | 0 | 0 | 1 |
| Real Estate | 4,988 | 0.001 | 0.028 | 0 | 0 | 0 | 1 |
| Technology | 4,988 | 0.008 | 0.087 | 0 | 0 | 0 | 1 |
| Utilities | 4,988 | 0.014 | 0.118 | 0 | 0 | 0 | 1 |
| AUD | 4,988 | 0.014 | 0.118 | 0 | 0 | 0 | 1 |
| CAD | 4,988 | 0.004 | 0.066 | 0 | 0 | 0 | 1 |
| CLP | 4,988 | 0.0004 | 0.020 | 0 | 0 | 0 | 1 |
| CNY | 4,988 | 0.0002 | 0.014 | 0 | 0 | 0 | 1 |
| EUR | 4,988 | 0.528 | 0.499 | 0 | 0 | 1 | 1 |
| GBP | 4,988 | 0.062 | 0.242 | 0 | 0 | 0 | 1 |
| HKD | 4,988 | 0.0002 | 0.014 | 0 | 0 | 0 | 1 |
| JPY | 4,988 | 0.021 | 0.145 | 0 | 0 | 0 | 1 |
| NZD | 4,988 | 0.001 | 0.028 | 0 | 0 | 0 | 1 |
| NOK | 4,988 | 0.0004 | 0.020 | 0 | 0 | 0 | 1 |
| SEK | 4,988 | 0.0002 | 0.014 | 0 | 0 | 0 | 1 |
| USD | 4,988 | 0.364 | 0.481 | 0 | 0 | 1 | 1 |
| UYU | 4,988 | 0.0004 | 0.020 | 0 | 0 | 0 | 1 |
| Senior Secured Mortgage | 4,988 | 0.088 | 0.284 | 0 | 0 | 0 | 1 |
| Senior Secured | 4,988 | 0.059 | 0.235 | 0 | 0 | 0 | 1 |
| Senior Unsecured | 4,988 | 0.647 | 0.478 | 0 | 0 | 1 | 1 |
| Senior Non-Preferred | 4,988 | 0.029 | 0.167 | 0 | 0 | 0 | 1 |
| Senior Preferred | 4,988 | 0.048 | 0.214 | 0 | 0 | 0 | 1 |
| Senior Subordinated Unsecured | 4,988 | 0.002 | 0.049 | 0 | 0 | 0 | 1 |
| Subordinated Unsecured | 4,988 | 0.020 | 0.141 | 0 | 0 | 0 | 1 |
| Unsecured | 4,988 | 0.090 | 0.286 | 0 | 0 | 0 | 1 |
| Public Sector | 4,988 | 0.504 | 0.500 | 0 | 0 | 1 | 1 |
| Corporate Sector | 4,988 | 0.496 | 0.500 | 0 | 0 | 1 | 1 |

### B.1.2 Raincloud Plots

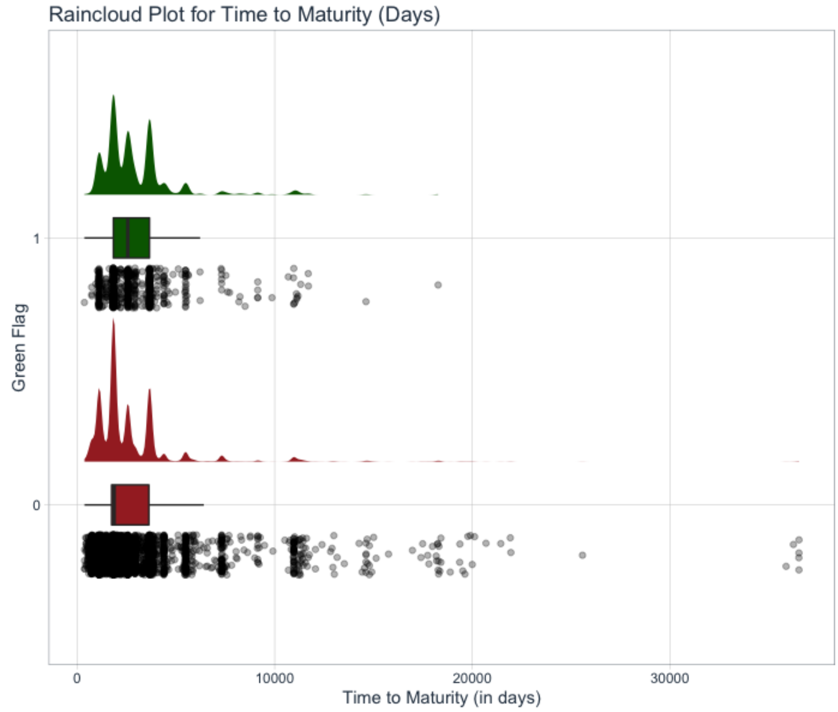



Figure 13: Raincloud Plot for Time to Maturity (Days)

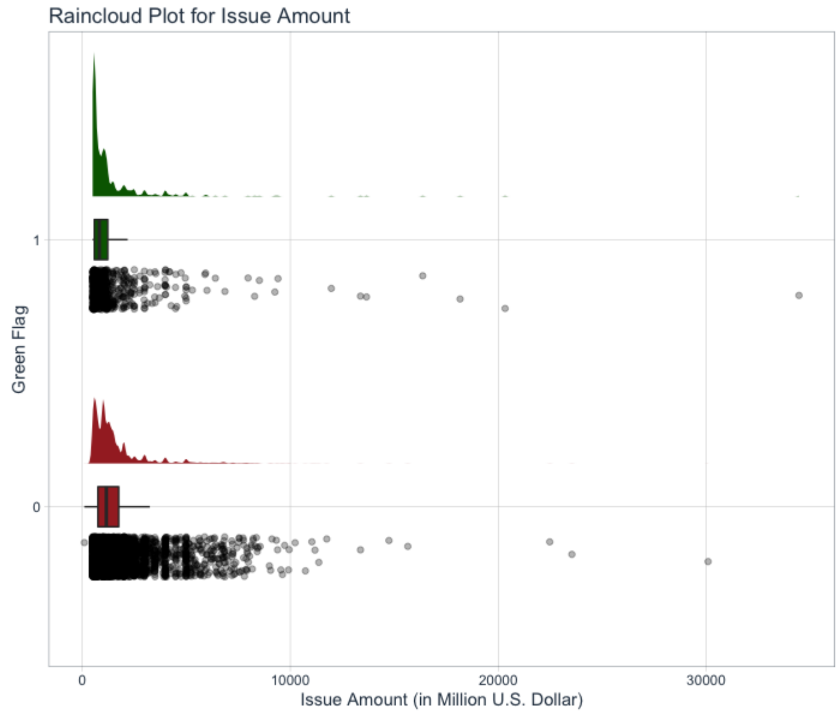



Figure 14: Raincloud for Issue Amount

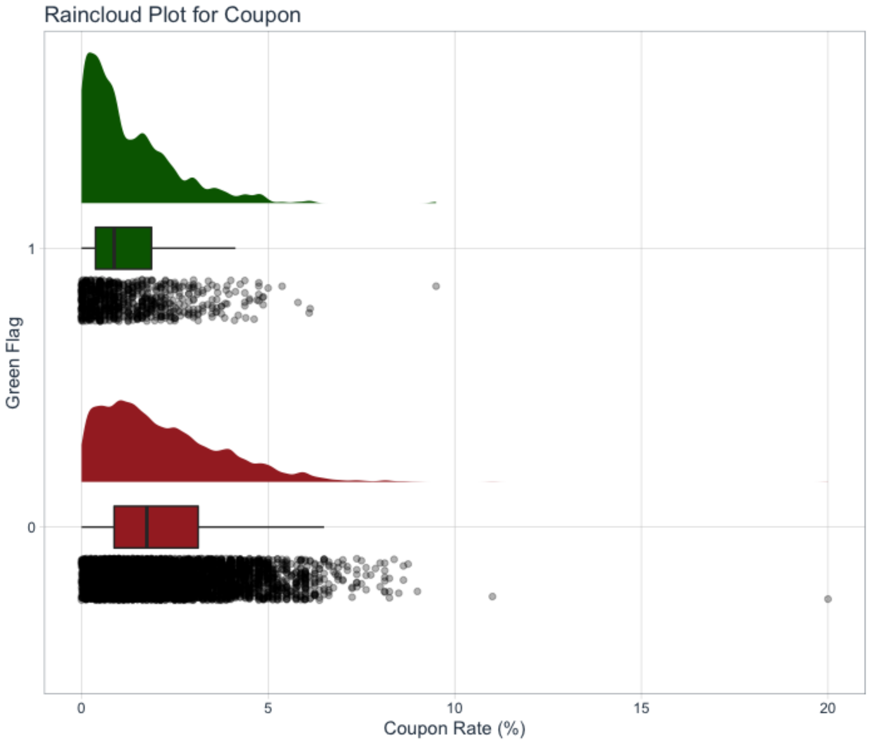



Figure 15: Raincloud for Coupon Rate

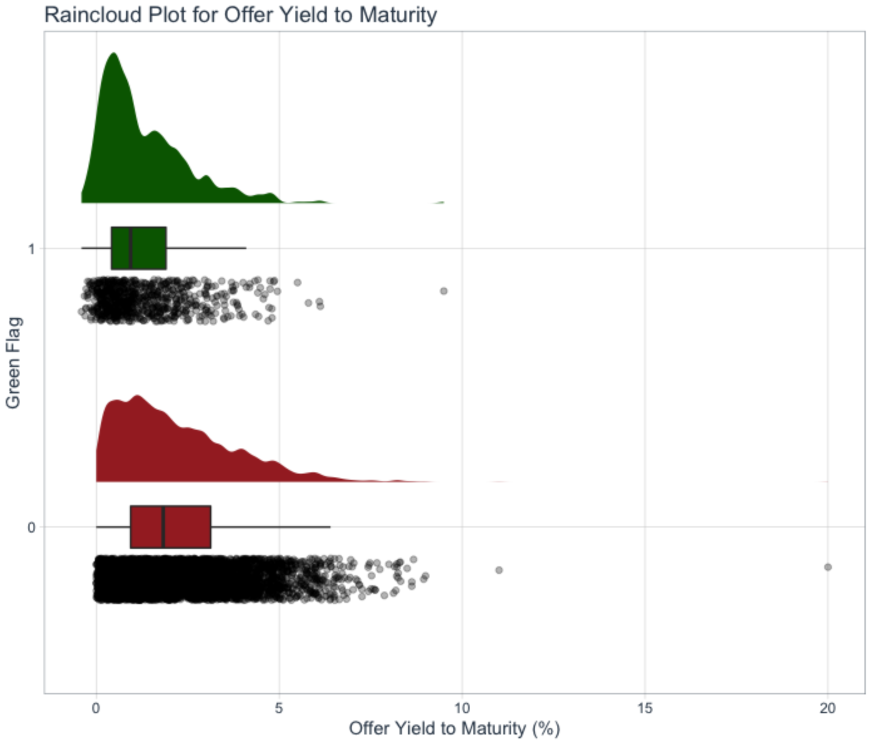



Figure 16: Raincloud for Issuance Yield

### B.1.3 Correlation

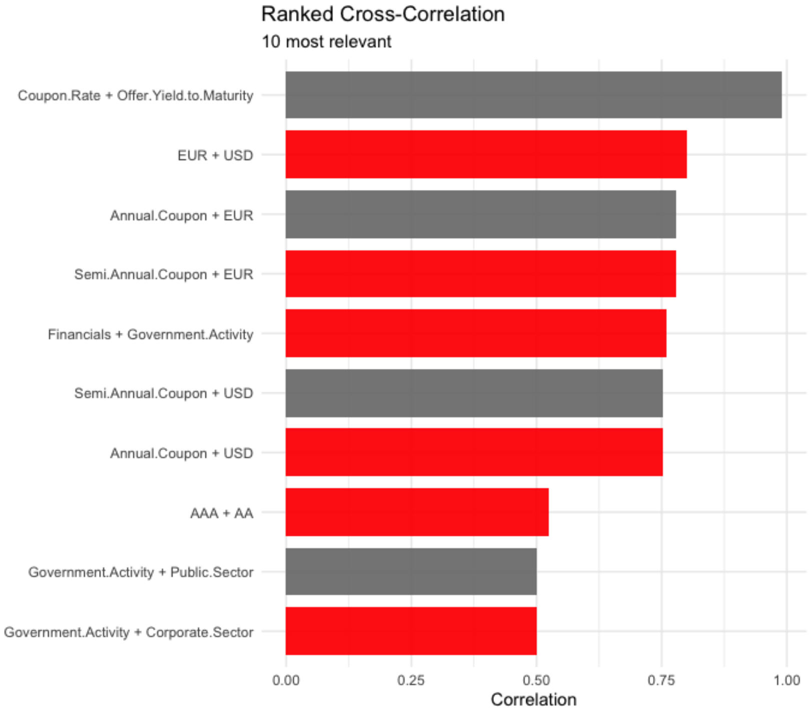



Figure 17: Ranked Cross-Correlation of 10 Most Relevant Pairs

Note: Blue = Positive Correlation, Red = Negative Correlation.

### B.1.4 Propensity Tables

| Issue Year | Green (%) | Brown (%) |
|---|---|---|
| 2008 | 0.0 | 4.6 |
| 2009 | 0.0 | 5.7 |
| 2010 | 0.0 | 6.9 |
| 2011 | 0.0 | 7.4 |
| 2012 | 0.1 | 9.0 |
| 2013 | 1.1 | 7.5 |
| 2014 | 1.2 | 7.6 |
| 2015 | 3.6 | 8.1 |
| 2016 | 4.6 | 8.2 |
| 2017 | 7.3 | 7.1 |
| 2018 | 8.5 | 6.8 |
| 2019 | 12.7 | 7.3 |
| 2020 | 17.0 | 5.1 |
| 2021 | 24.7 | 4.2 |
| 2022 | 19.1 | 4.6 |

(a) Issue Year

| Rating | Green (%) | Brown (%) |
|---|---|---|
| AAA | 34.1 | 45.0 |
| AA | 20.7 | 27.0 |
| A | 22.7 | 13.9 |
| BBB | 21.1 | 12.7 |
| BB | 1.2 | 1.2 |
| B | 0.3 | 0.2 |
| CCC | 0.0 | 0.0 |

(b) Rating

Table 22: Propensity Tables

Table 23: Propensity Table for Coupon Frequency

| Coupon Frequency | Green (%) | Brown (%) |
|---|---|---|
| Annual Coupon | 68.2 | 63.1 |
| Semi Annual Coupon | 31.6 | 36.6 |
| Quarterly | 0.0 | 0.2 |
| Maturity | 0.1 | 0.1 |

Table 24: Propensity Table for Industry

| TRBC Industry | Green (%) | Brown (%) |
|---|---|---|
| Academic & Educational Services | 0.0 | 0.0 |
| Basic Materials | 1.4 | 0.5 |
| Consumer Cyclicals | 0.8 | 0.6 |
| Consumer Non-Cyclicals | 0.8 | 0.2 |
| Energy | 0.3 | 0.5 |
| Financials | 56.9 | 67.5 |
| Government Activity | 19.5 | 23.3 |
| Healthcare | 0.3 | 0.1 |
| Industrials | 4.5 | 1.1 |
| Institutions, Associations & Organizations | 8.4 | 3.8 |
| Real Estate | 1.8 | 0.1 |
| Technology | 0.9 | 0.8 |
| Utilities | 4.6 | 1.4 |

Table 25: Propensity Table for Currency

| Currency | Green (%) | Brown (%) | | Green (%) | Brown (%) |
|---|---|---|---|---|---|
| AUD | 0.4 | 1.4 | NZD | 0.3 | 0.1 |
| BRL | 0.0 | 0.0 | NOK | 0.1 | 0.0 |
| CAD | 2.6 | 0.4 | PEN | 0.0 | 0.0 |
| CLP | 0.1 | 0.0 | PHP | 0.0 | 0.0 |
| CNY | 0.1 | 0.0 | RUB | 0.0 | 0.0 |
| COP | 0.0 | 0.0 | SGD | 0.0 | 0.0 |
| HRK | 0.0 | 0.0 | SEK | 1.2 | 0.0 |
| EUR | 61.8 | 52.8 | CHF | 0.0 | 0.2 |
| GBP | 3.0 | 6.2 | THB | 0.0 | 0.0 |
| HKD | 0.1 | 0.0 | TRY | 0.0 | 0.0 |
| JPY | 1.8 | 2.1 | USD | 28.4 | 36.4 |
| KZT | 0.0 | 0.0 | UYU | 0.1 | 0.0 |
| MXN | 0.0 | 0.0 | | | |

| Issuer Sector | Green (%) | Brown (%) |
|---|---|---|
| Public Sector | 48.2 | 50.4 |
| Corporate Sector | 51.8 | 49.6 |

(a) Issuer Sector

| Guarantor | Green (%) | Brown (%) |
|---|---|---|
| Guarantor | 14.3 | 18.6 |
| No Guarantor | 85.7 | 81.4 |

(b) Guarantor

Table 26: Propensity Table for Issuer Sector and Guarantor

Table 27: Propensity Table for Seniority

| Seniority | Green (%) | Brown (%) |
|---|---|---|
| First-Lien Loan | 0.0 | 0.0 |
| First Mortgage | 0.0 | 0.0 |
| First Refunding Mortgage | 0.0 | 0.0 |
| Second-Lien Loan | 0.0 | 0.0 |
| Junior Subordinated | 0.0 | 0.0 |
| Senior Secured Mortgage | 6.4 | 8.8 |
| Refunding Mortgage | 0.0 | 0.0 |
| Senior Secured | 73.2 | 64.7 |
| Senior Unsecured | 5.7 | 2.9 |
| Senior Non-Preferred | 6.9 | 4.8 |
| Senior Preferred | 3.6 | 0.5 |
| Senior Subordinated Unsecured | 0.1 | 0.2 |
| Senior Subordinated Secured | 0.0 | 0.0 |
| Subordinated Unsecured | 0.7 | 2.0 |
| Subordinated Secured | 0.0 | 0.0 |
| Unsecured | 3.2 | 9.0 |

## B.2 Causal Forest

### B.2.1 Without Issuer Controls

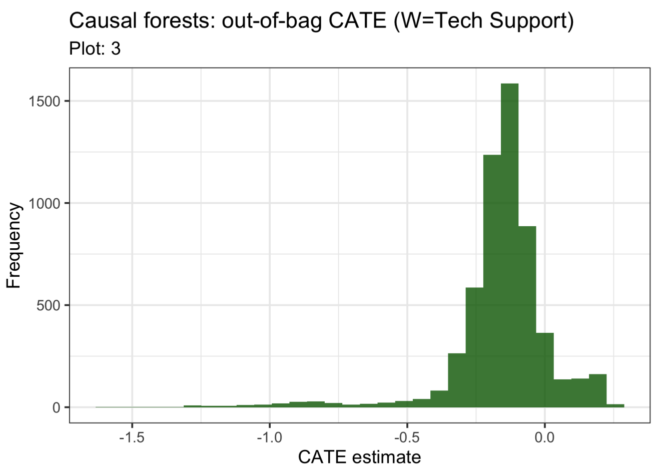



Figure 18: Distribution of CATE (Model 3)

#### B.2.1.1 Nuisance Parameter Check

| | *Dependent variable: Green Flag* |
|---|---|
| e.bar | 1.002*** |
| | (0.029) |
| e.residual | 1.139*** |
| | (0.035) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(a) Outcome Model

| | *Dependent variable: Green Flag* |
|---|---|
| m.bar | 1.001*** |
| | (0.010) |
| m.residual | 1.206*** |
| | (0.014) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(b) Propensity Model

Table 28: Calibration Regressions (Model 3)

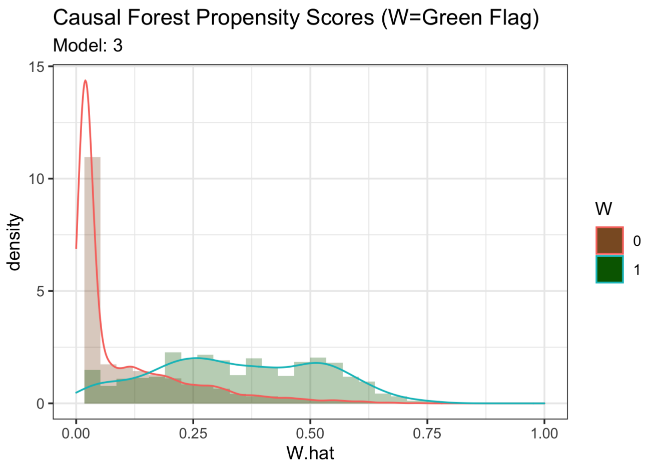



Figure 19: Propensity Score Distribution (Model 3)

#### B.2.1.2 Heterogeneity Assessment

Table 29: Variable Importance (Model 3)

| Covariate | Value |
|---|---|
| 2022 | 0.23194018 |
| Issue Amount | 0.21746960 |
| Time to Maturity (Days) | 0.18983740 |
| 2021 | 0.07048934 |
| 2020 | 0.05790504 |
| A | 0.03261894 |

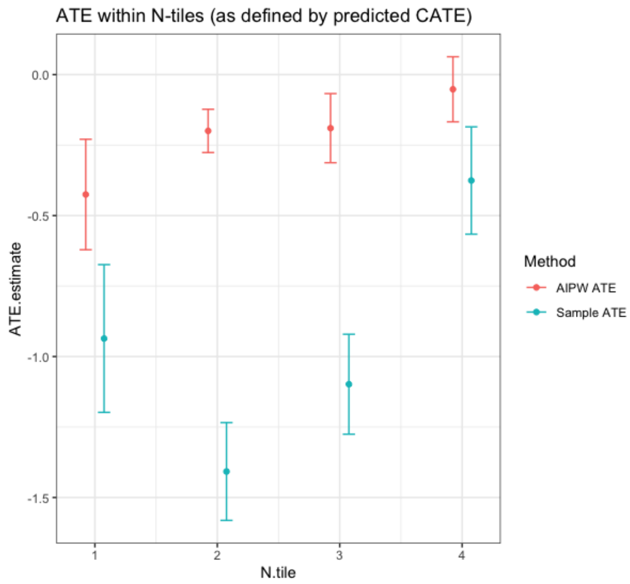
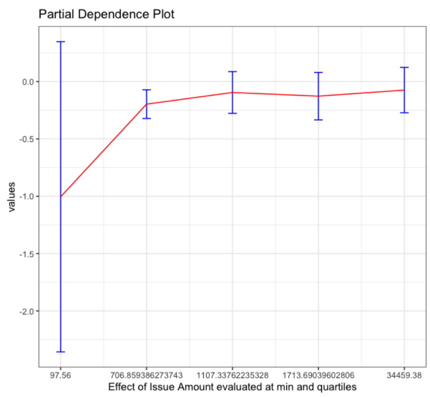
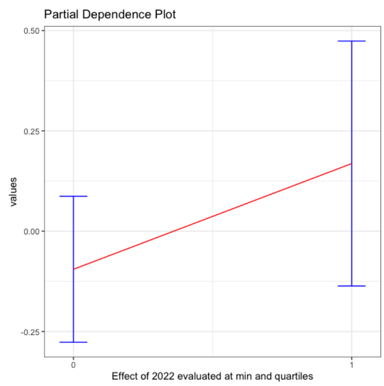


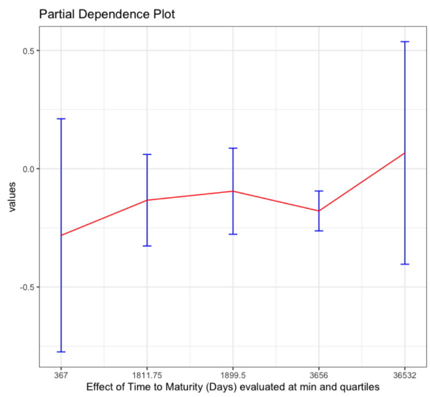

Figure 20: Graph of ATE within Subgroups (Model 3)




(a) Effect of Issue Amount




(b) Effect of 2022




(c) Effect of Time to Maturity (Days)

Figure 21: Partial Dependency Plots (Model 3)

## Appendix C: Issuer matched EUR/USD Dataset Analysis

# C.1 Descriptive Statistics

## C.1.1 Summary Statistics

Table 30: Data Matched USDEUR Green Bond Summary Statistics

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Time to Maturity (Days) | 663 | 2,997.576 | 1,968.983 | 367 | 1,833 | 3,660 | 18,269 |
| Issue Amount | 663 | 1,396.167 | 2,145.963 | 500.000 | 571.474 | 1,242.435 | 33,563.640 |
| Coupon Rate | 663 | 1.263 | 1.211 | 0.000 | 0.375 | 1.812 | 9.500 |
| Guarantor | 663 | 0.140 | 0.348 | 0 | 0 | 0 | 1 |
| Offer Yield to Maturity | 663 | 1.306 | 1.224 | −0.403 | 0.440 | 1.893 | 9.500 |
| Green Flag | 663 | 1.000 | 0.000 | 1 | 1 | 1 | 1 |
| 2008 | 663 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2009 | 663 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2010 | 663 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2011 | 663 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2012 | 663 | 0.002 | 0.039 | 0 | 0 | 0 | 1 |
| 2013 | 663 | 0.012 | 0.109 | 0 | 0 | 0 | 1 |
| 2014 | 663 | 0.012 | 0.109 | 0 | 0 | 0 | 1 |
| 2015 | 663 | 0.038 | 0.191 | 0 | 0 | 0 | 1 |
| 2016 | 663 | 0.048 | 0.214 | 0 | 0 | 0 | 1 |
| 2017 | 663 | 0.078 | 0.269 | 0 | 0 | 0 | 1 |
| 2018 | 663 | 0.086 | 0.281 | 0 | 0 | 0 | 1 |
| 2019 | 663 | 0.130 | 0.336 | 0 | 0 | 0 | 1 |
| 2020 | 663 | 0.164 | 0.371 | 0 | 0 | 0 | 1 |
| 2021 | 663 | 0.237 | 0.425 | 0 | 0 | 0 | 1 |
| 2022 | 663 | 0.193 | 0.395 | 0 | 0 | 0 | 1 |
| AAA | 663 | 0.312 | 0.464 | 0 | 0 | 1 | 1 |
| AA | 663 | 0.214 | 0.411 | 0 | 0 | 0 | 1 |
| A | 663 | 0.228 | 0.420 | 0 | 0 | 0 | 1 |
| BBB | 663 | 0.229 | 0.421 | 0 | 0 | 0 | 1 |
| BB | 663 | 0.014 | 0.116 | 0 | 0 | 0 | 1 |
| B | 663 | 0.003 | 0.055 | 0 | 0 | 0 | 1 |
| EUR | 663 | 0.688 | 0.464 | 0 | 0 | 1 | 1 |
| USD | 663 | 0.312 | 0.464 | 0 | 0 | 1 | 1 |
| Annual Coupon | 663 | 0.716 | 0.451 | 0 | 0 | 1 | 1 |
| Semi Annual Coupon | 663 | 0.282 | 0.450 | 0 | 0 | 1 | 1 |
| Quarterly | 663 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| Maturity | 663 | 0.002 | 0.039 | 0 | 0 | 0 | 1 |

Table 31: Data Matched USDEUR Green Bond Summary Statistics cont.

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Basic Materials | 663 | 0.015 | 0.122 | 0 | 0 | 0 | 1 |
| Consumer Cyclicals | 663 | 0.006 | 0.077 | 0 | 0 | 0 | 1 |
| Consumer Non-Cyclicals | 663 | 0.008 | 0.087 | 0 | 0 | 0 | 1 |
| Energy | 663 | 0.003 | 0.055 | 0 | 0 | 0 | 1 |
| Financials | 663 | 0.596 | 0.491 | 0 | 0 | 1 | 1 |
| Government Activity | 663 | 0.195 | 0.396 | 0 | 0 | 0 | 1 |
| Healthcare | 663 | 0.003 | 0.055 | 0 | 0 | 0 | 1 |
| Industrials | 663 | 0.033 | 0.179 | 0 | 0 | 0 | 1 |
| Institutions, Associations & Organizations | 663 | 0.066 | 0.249 | 0 | 0 | 0 | 1 |
| Real Estate | 663 | 0.020 | 0.139 | 0 | 0 | 0 | 1 |
| Technology | 663 | 0.006 | 0.077 | 0 | 0 | 0 | 1 |
| Utilities | 663 | 0.050 | 0.218 | 0 | 0 | 0 | 1 |
| Senior Secured Mortgage | 663 | 0.069 | 0.254 | 0 | 0 | 0 | 1 |
| Senior Secured | 663 | 0.026 | 0.158 | 0 | 0 | 0 | 1 |
| Senior Unsecured | 663 | 0.732 | 0.444 | 0 | 0 | 1 | 1 |
| Senior Non-Preferred | 663 | 0.060 | 0.238 | 0 | 0 | 0 | 1 |
| Senior Preferred | 663 | 0.077 | 0.267 | 0 | 0 | 0 | 1 |
| Senior Subordinated Unsecured | 663 | 0.002 | 0.039 | 0 | 0 | 0 | 1 |
| Subordinated Unsecured | 663 | 0.008 | 0.087 | 0 | 0 | 0 | 1 |
| Unsecured | 663 | 0.026 | 0.158 | 0 | 0 | 0 | 1 |
| Public Sector | 663 | 0.460 | 0.499 | 0 | 0 | 1 | 1 |
| Corporate Sector | 663 | 0.540 | 0.499 | 0 | 0 | 1 | 1 |

Table 32: Data Matched USDEUR Brown Bond Summary Statistics

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Time to Maturity (Days) | 4,349 | 2,632.082 | 2,248.019 | 373 | 1,759 | 3,613 | 36,532 |
| Issue Amount | 4,349 | 1,631.361 | 1,491.449 | 500 | 838.7 | 1,775.0 | 30,089 |
| Coupon Rate | 4,349 | 2.117 | 1.525 | 0.010 | 0.875 | 3.000 | 9.000 |
| Guarantor | 4,349 | 0.187 | 0.390 | 0 | 0 | 0 | 1 |
| Offer Yield to Maturity | 4,349 | 2.152 | 1.530 | 0.004 | 0.942 | 3.060 | 9.000 |
| Green Flag | 4,349 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2008 | 4,349 | 0.046 | 0.209 | 0 | 0 | 0 | 1 |
| 2009 | 4,349 | 0.054 | 0.226 | 0 | 0 | 0 | 1 |
| 2010 | 4,349 | 0.070 | 0.255 | 0 | 0 | 0 | 1 |
| 2011 | 4,349 | 0.074 | 0.262 | 0 | 0 | 0 | 1 |
| 2012 | 4,349 | 0.088 | 0.283 | 0 | 0 | 0 | 1 |
| 2013 | 4,349 | 0.079 | 0.269 | 0 | 0 | 0 | 1 |

Table 33: Data Matched USDEUR Brown Bond Summary Statistics cont.

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| 2014 | 4,349 | 0.077 | 0.267 | 0 | 0 | 0 | 1 |
| 2015 | 4,349 | 0.082 | 0.275 | 0 | 0 | 0 | 1 |
| 2016 | 4,349 | 0.084 | 0.277 | 0 | 0 | 0 | 1 |
| 2017 | 4,349 | 0.072 | 0.259 | 0 | 0 | 0 | 1 |
| 2018 | 4,349 | 0.068 | 0.252 | 0 | 0 | 0 | 1 |
| 2019 | 4,349 | 0.073 | 0.260 | 0 | 0 | 0 | 1 |
| 2020 | 4,349 | 0.048 | 0.214 | 0 | 0 | 0 | 1 |
| 2021 | 4,349 | 0.037 | 0.188 | 0 | 0 | 0 | 1 |
| 2022 | 4,349 | 0.047 | 0.212 | 0 | 0 | 0 | 1 |
| AAA | 4,349 | 0.458 | 0.498 | 0 | 0 | 1 | 1 |
| AA | 4,349 | 0.254 | 0.435 | 0 | 0 | 1 | 1 |
| A | 4,349 | 0.139 | 0.346 | 0 | 0 | 0 | 1 |
| BBB | 4,349 | 0.133 | 0.340 | 0 | 0 | 0 | 1 |
| BB | 4,349 | 0.013 | 0.114 | 0 | 0 | 0 | 1 |
| B | 4,349 | 0.002 | 0.048 | 0 | 0 | 0 | 1 |
| EUR | 4,349 | 0.599 | 0.490 | 0 | 0 | 1 | 1 |
| USD | 4,349 | 0.401 | 0.490 | 0 | 0 | 1 | 1 |
| Annual Coupon | 4,349 | 0.652 | 0.477 | 0 | 0 | 1 | 1 |
| Semi Annual Coupon | 4,349 | 0.346 | 0.476 | 0 | 0 | 1 | 1 |
| Quarterly | 4,349 | 0.002 | 0.040 | 0 | 0 | 0 | 1 |
| Maturity | 4,349 | 0.001 | 0.026 | 0 | 0 | 0 | 1 |
| Basic Materials | 4,349 | 0.006 | 0.074 | 0 | 0 | 0 | 1 |
| Consumer Cyclicals | 4,349 | 0.005 | 0.073 | 0 | 0 | 0 | 1 |
| Consumer Non-Cyclicals | 4,349 | 0.002 | 0.045 | 0 | 0 | 0 | 1 |
| Energy | 4,349 | 0.006 | 0.076 | 0 | 0 | 0 | 1 |
| Financials | 4,349 | 0.705 | 0.456 | 0 | 0 | 1 | 1 |
| Government Activity | 4,349 | 0.211 | 0.408 | 0 | 0 | 0 | 1 |
| Healthcare | 4,349 | 0.001 | 0.026 | 0 | 0 | 0 | 1 |
| Industrials | 4,349 | 0.008 | 0.087 | 0 | 0 | 0 | 1 |
| Institutions, Associations & Organizations | 4,349 | 0.036 | 0.187 | 0 | 0 | 0 | 1 |
| Real Estate | 4,349 | 0.001 | 0.030 | 0 | 0 | 0 | 1 |
| Technology | 4,349 | 0.007 | 0.083 | 0 | 0 | 0 | 1 |
| Utilities | 4,349 | 0.014 | 0.116 | 0 | 0 | 0 | 1 |
| Senior Secured Mortgage | 4,349 | 0.100 | 0.300 | 0 | 0 | 0 | 1 |
| Senior Secured | 4,349 | 0.057 | 0.231 | 0 | 0 | 0 | 1 |
| Senior Unsecured | 4,349 | 0.647 | 0.478 | 0 | 0 | 1 | 1 |
| Senior Non-Preferred | 4,349 | 0.029 | 0.168 | 0 | 0 | 0 | 1 |
| Senior Preferred | 4,349 | 0.051 | 0.220 | 0 | 0 | 0 | 1 |
| Senior Subordinated Unsecured | 4,349 | 0.003 | 0.052 | 0 | 0 | 0 | 1 |
| Subordinated Unsecured | 4,349 | 0.023 | 0.148 | 0 | 0 | 0 | 1 |
| Unsecured | 4,349 | 0.073 | 0.261 | 0 | 0 | 0 | 1 |
| Public Sector | 4,349 | 0.487 | 0.500 | 0 | 0 | 1 | 1 |
| Corporate Sector | 4,349 | 0.513 | 0.500 | 0 | 0 | 1 | 1 |

### C.1.2 Raincloud Plots

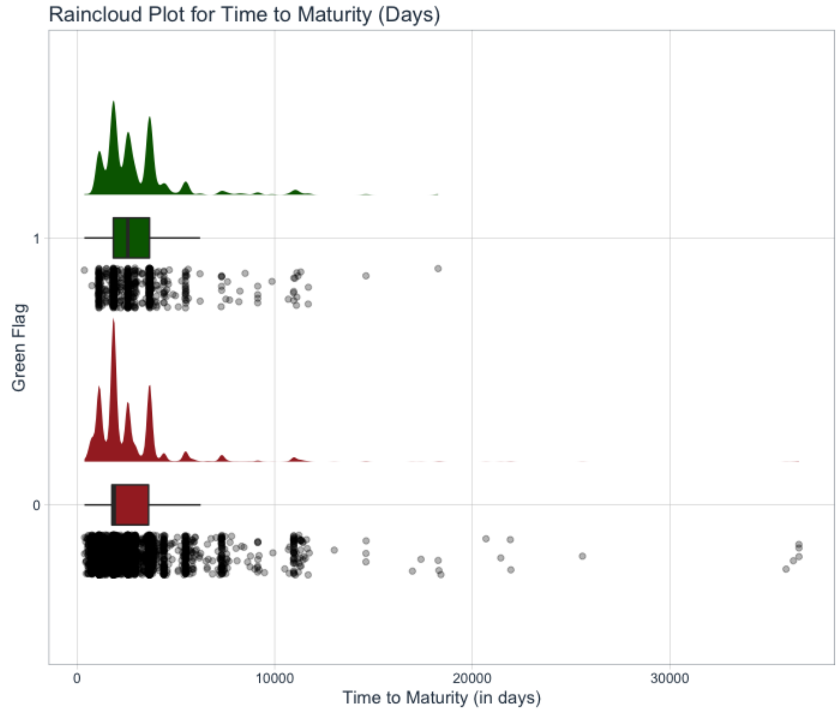



Figure 22: Raincloud Plot for Time to Maturity (Days)

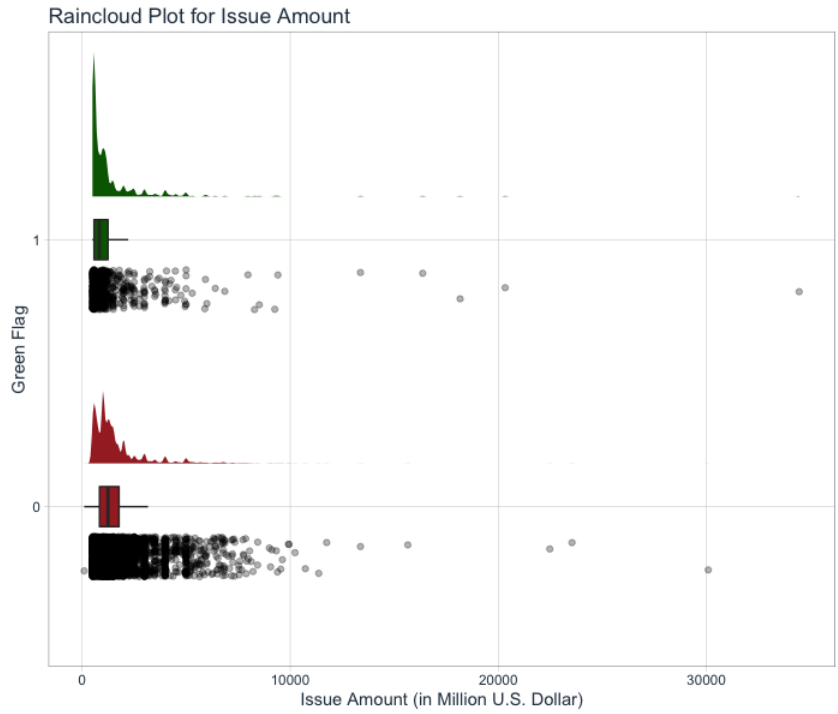



Figure 23: Raincloud for Issue Amount

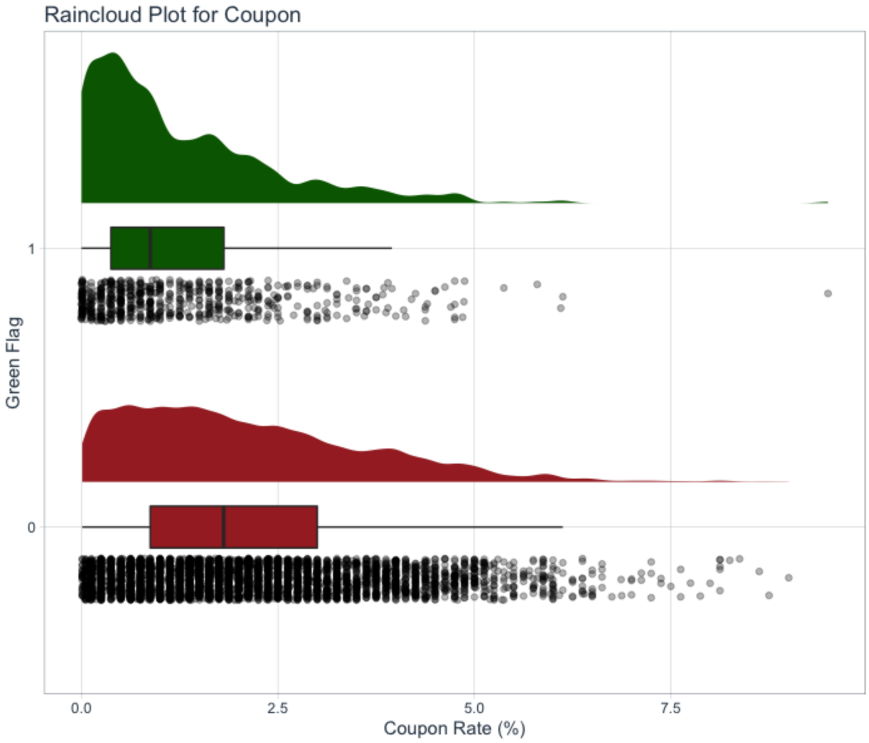



Figure 24: Raincloud for Coupon Rate

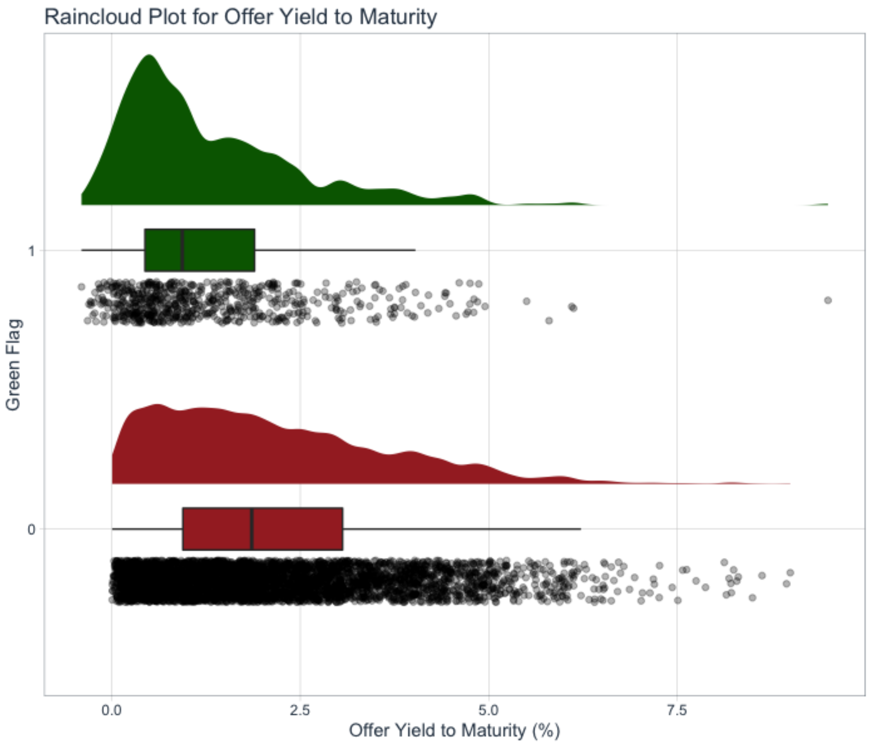



Figure 25: Raincloud for Issuance Yield

### C.1.3 Correlation

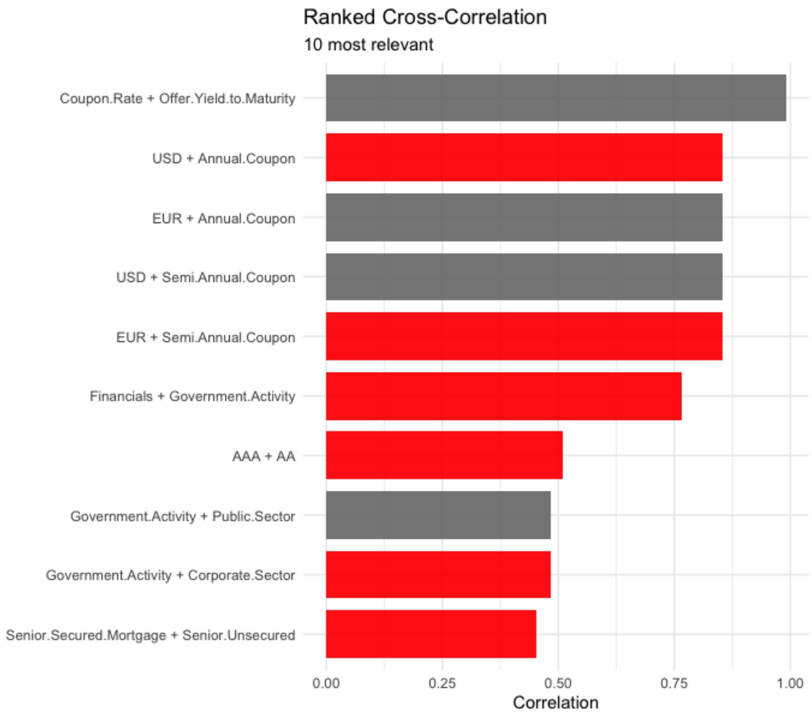



Figure 26: Ranked Cross-Correlation of 10 Most Relevant Pairs

Note: Blue = Positive Correlation, Red = Negative Correlation.

### C.1.4 Propensity Tables

| Issue Year | Green (%) | Brown (%) |
|---|---|---|
| 2008 | 0.0 | 4.6 |
| 2009 | 0.0 | 5.4 |
| 2010 | 0.0 | 7.0 |
| 2011 | 0.0 | 7.4 |
| 2012 | 0.2 | 8.8 |
| 2013 | 1.2 | 7.9 |
| 2014 | 1.2 | 7.7 |
| 2015 | 3.8 | 8.2 |
| 2016 | 4.8 | 8.4 |
| 2017 | 7.8 | 7.2 |
| 2018 | 8.6 | 6.8 |
| 2019 | 13.0 | 7.3 |
| 2020 | 16.4 | 4.8 |
| 2021 | 23.7 | 3.7 |
| 2022 | 19.3 | 4.7 |

(a) Issue Year

| Rating | Green (%) | Brown (%) |
|---|---|---|
| AAA | 31.2 | 45.8 |
| AA | 21.4 | 25.4 |
| A | 22.8 | 13.9 |
| BBB | 22.9 | 13.3 |
| BB | 1.4 | 1.3 |
| B | 0.3 | 0.2 |
| CCC | 0.0 | 0.0 |

(b) Rating

Table 34: Propensity Tables

Table 35: Propensity Table for Coupon Frequency

| Coupon Frequency | Green (%) | Brown (%) |
|---|---|---|
| Annual Coupon | 71.6 | 65.2 |
| Semi Annual Coupon | 28.2 | 34.6 |
| Quarterly | 0.0 | 0.2 |
| Maturity | 0.2 | 0.1 |

Table 36: Propensity Table for Industry

| TRBC Industry | Green (%) | Brown (%) |
|---|---|---|
| Academic & Educational Services | 0.0 | 0.0 |
| Basic Materials | 1.5 | 0.6 |
| Consumer Cyclicals | 0.6 | 0.5 |
| Consumer Non-Cyclicals | 0.8 | 0.2 |
| Energy | 0.3 | 0.6 |
| Financials | 59.6 | 70.5 |
| Government Activity | 19.5 | 21.1 |
| Healthcare | 0.3 | 0.1 |
| Industrials | 3.3 | 0.8 |
| Institutions, Associations & Organizations | 6.6 | 3.8 |
| Real Estate | 2.0 | 0.1 |
| Technology | 0.6 | 0.7 |
| Utilities | 5.0 | 1.4 |

Table 37: Propensity Table for Currency

| Currency | Green (%) | Brown (%) |
|---|---|---|
| USD | 68.8 | 59.9 |
| EUR | 31.2 | 40.1 |

Table 38: Propensity Table for Seniority

| Seniority | Green (%) | Brown (%) |
|---|---|---|
| First-Lien Loan | 0.0 | 0.0 |
| First Mortgage | 0.0 | 0.0 |
| First Refunding Mortgage | 0.0 | 0.0 |
| Second-Lien Loan | 0.0 | 0.0 |
| Junior Subordinated | 0.0 | 0.0 |
| Senior Secured Mortgage | 6.9 | 10.0 |
| Refunding Mortgage | 0.0 | 0.0 |
| Senior Secured | 73.2 | 64.7 |
| Senior Unsecured | 6.0 | 2.9 |
| Senior Non-Preferred | 7.7 | 5.1 |
| Senior Preferred | 2.6 | 5.7 |
| Senior Subordinated Unsecured | 0.2 | 0.3 |
| Senior Subordinated Secured | 0.0 | 0.0 |
| Subordinated Unsecured | 0.8 | 2.3 |
| Subordinated Secured | 0.0 | 0.0 |
| Unsecured | 2.6 | 7.3 |

| Issuer Sector | Green (%) | Brown (%) |
|---|---|---|
| Public Sector | 54.0 | 46.0 |
| Corporate Sector | 51.3 | 48.7 |

(a) Issuer Sector

| Guarantor | Green (%) | Brown (%) |
|---|---|---|
| Guarantor | 14.0 | 18.7 |
| No Guarantor | 86.0 | 81.3 |

(b) Guarantor

Table 39: Propensity Table for Issuer Sector and Guarantor

## C.2 Causal Forest

### C.2.1 Without Issuer Controls

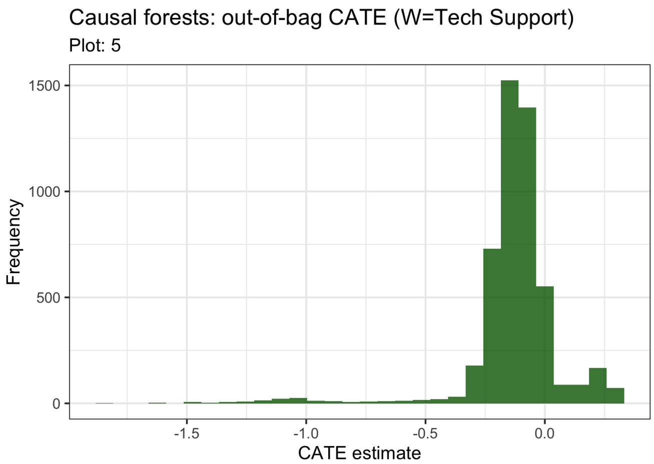



Figure 27: Distribution of CATE (Model 5)

#### C.2.1.1 Nuisance Parameter Check

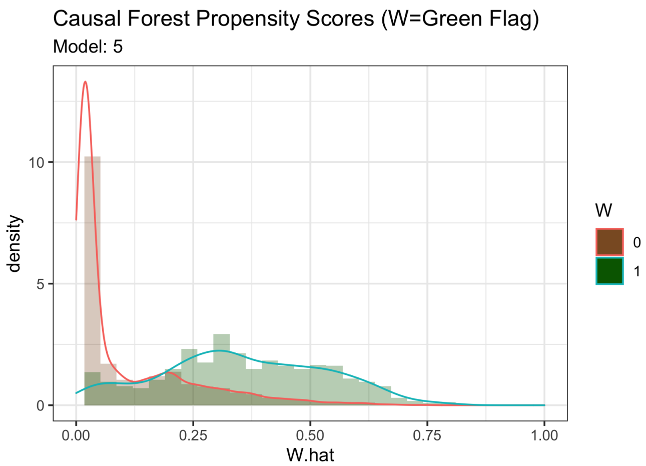



Figure 28: Propensity Score Distribution (Model 5)

| | Dependent variable: Green Flag |
|---|---|
| e.bar | 1.002*** |
| | (0.031) |
| e.residual | 1.117*** |
| | (0.036) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(a) Outcome Model

| | Dependent variable: Green Flag |
|---|---|
| m.bar | 1.001*** |
| | (0.011) |
| m.residual | 1.160*** |
| | (0.017) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(b) Propensity Model

Table 40: Calibration Regressions (Model 5)

#### C.2.1.2 Heterogeneity Assessment

Table 41: Variable Importance (Model 5)

| Covariate | Value |
|---|---|
| 2022 | 0.30362660 |
| Issue Amount | 0.22873726 |
| Time to Maturity (Days) | 0.17635279 |
| 2021 | 0.05021639 |
| 2020 | 0.04394978 |
| A | 0.03701316 |

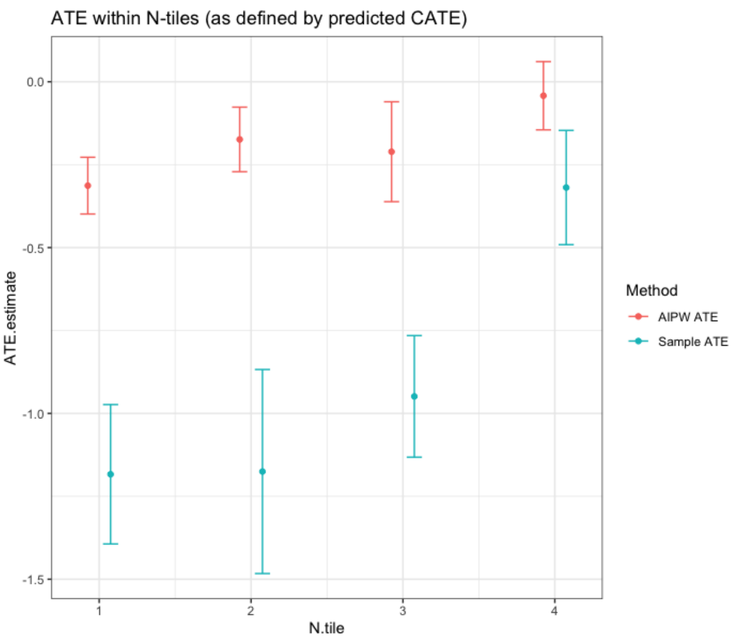
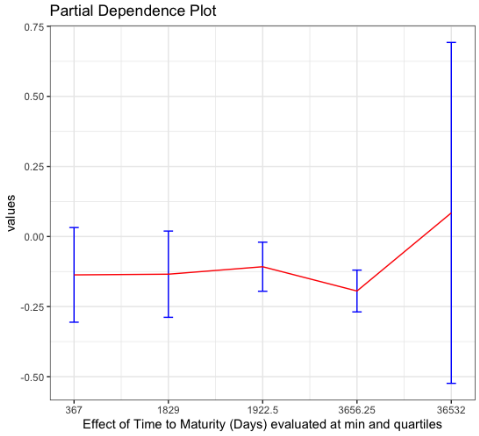
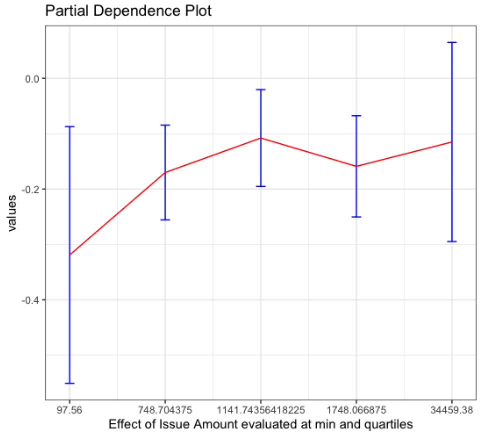


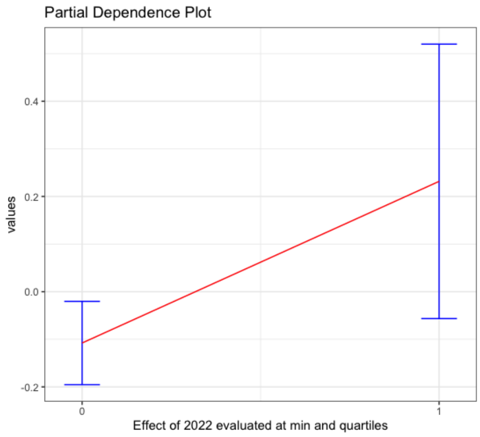

Figure 29: Graph of ATE within Subgroups (Model 5)




(a) Effect of Time to Maturity (Days)




(b) Effect of Issue Amount




(c) Effect of 2022

Figure 30: Partial Dependency Plots (Model 5)

Table 42: Heterogeneity across Covariates (Model 5)

| Variable | Mean ntile1 | Mean ntile2 | Mean ntile3 | Mean ntile4 |
|---|---|---|---|---|
| Time to Maturity (Days) | 2910.99 | 2426.86 | 2390.91 | 2992.96 |
| Issue Amount | 1160.36 | 1571.18 | 1962.16 | 1690.74 |
| Guarantor | 0.14 | 0.17 | 0.15 | 0.26 |
| 2013 | 0.08 | 0.08 | 0.07 | 0.05 |
| 2014 | 0.09 | 0.08 | 0.07 | 0.04 |
| 2015 | 0.11 | 0.08 | 0.07 | 0.04 |
| 2016 | 0.12 | 0.08 | 0.06 | 0.06 |
| 2017 | 0.09 | 0.09 | 0.08 | 0.04 |
| 2018 | 0.02 | 0.07 | 0.12 | 0.07 |
| 2019 | 0.12 | 0.12 | 0.07 | 0.01 |
| 2020 | 0.01 | 0.02 | 0.09 | 0.14 |
| 2021 | 0 | 0.02 | 0.09 | 0.15 |
| 2022 | 0 | 0 | 0 | 0.27 |
| Annual Coupon | 0.86 | 0.8 | 0.57 | 0.41 |
| Semi Annual Coupon | 0.14 | 0.2 | 0.42 | 0.59 |
| Quarterly | 0 | 0 | 0 | 0 |
| Senior Secured Mortgage | 0.13 | 0.11 | 0.08 | 0.07 |
| Senior Secured | 0.07 | 0.05 | 0.04 | 0.06 |
| Senior Unsecured | 0.64 | 0.62 | 0.63 | 0.74 |
| Senior Non Preferred | 0.02 | 0.02 | 0.06 | 0.03 |
| Senior Preferred | 0.05 | 0.06 | 0.06 | 0.05 |
| Senior Subordinated Unsecured | 0.01 | 0 | 0 | 0 |
| Subordinated Unsecured | 0.03 | 0.03 | 0.01 | 0.01 |
| Basic Materials | 0.01 | 0 | 0 | 0.01 |
| Consumer Cyclicals | 0.01 | 0 | 0 | 0 |
| Consumer Non Cyclicals | 0 | 0 | 0 | 0 |
| Energy | 0.01 | 0.01 | 0 | 0 |
| Financials | 0.7 | 0.68 | 0.69 | 0.7 |
| Healthcare | 0 | 0 | 0 | 0 |
| Industrials | 0.02 | 0.01 | 0.01 | 0.01 |
| Institutions, Associations & Organizations | 0.02 | 0.03 | 0.07 | 0.04 |
| Real Estate | 0 | 0 | 0 | 0 |
| Technology | 0.01 | 0.01 | 0.01 | 0 |
| Utilities | 0.03 | 0.02 | 0.01 | 0.01 |
| AAA | 0.34 | 0.44 | 0.5 | 0.48 |
| AA | 0.28 | 0.21 | 0.19 | 0.31 |
| A | 0.24 | 0.16 | 0.1 | 0.11 |
| BBB | 0.12 | 0.17 | 0.2 | 0.09 |
| BB | 0.02 | 0.02 | 0.01 | 0.01 |
| EUR | 0.82 | 0.72 | 0.51 | 0.39 |

### C.2.2 With Issuer Controls

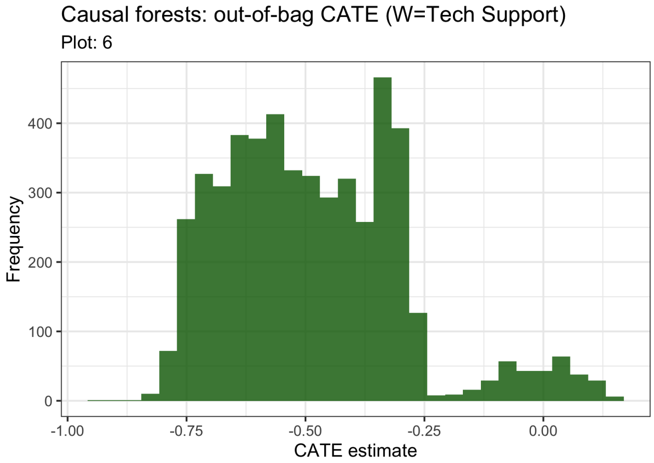



Figure 31: Distribution of CATE (Model 6)

#### C.2.2.1 Nuisance Parameter Check

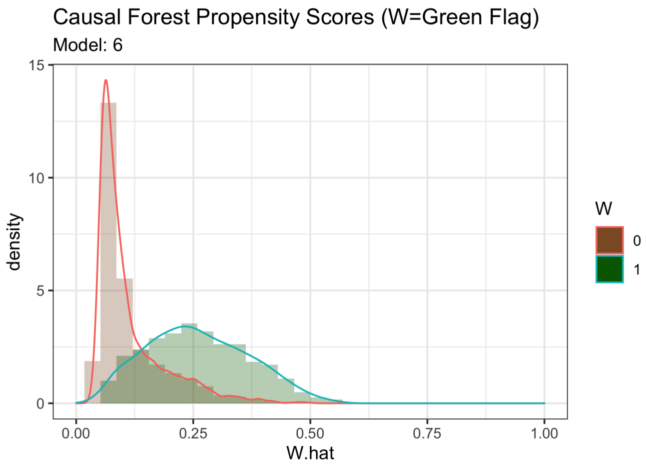



Figure 32: Propensity Score Distribution (Model 6)

| | *Dependent variable: Green Flag* |
|---|---|
| e.bar | 1.003*** |
| | (0.031) |
| e.residual | 1.946*** |
| | (0.061) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(a) Outcome Model

| | *Dependent variable: Green Flag* |
|---|---|
| m.bar | 1.000*** |
| | (0.012) |
| m.residual | 2.056*** |
| | (0.039) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(b) Propensity Model

Table 43: Calibration Regressions (Model 6)

#### C.2.2.2 Heterogeneity Assessment

Table 44: Variable Importance (Model 6)

| Covariate | Value |
|---|---|
| 2022 | 0.11191270 |
| Issue Amount | 0.10161593 |
| Time to Maturity (Days) | 0.09521301 |
| EUR | 0.06385172 |
| Annual Coupon | 0.06081552 |
| Semi Annual Coupon | 0.05372767 |

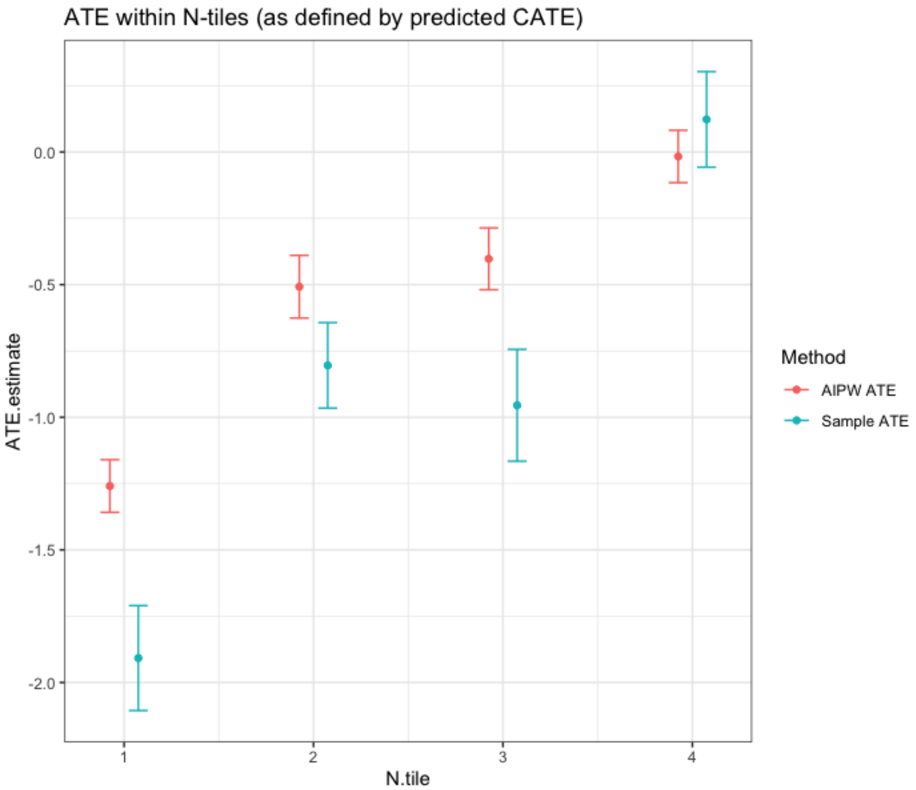
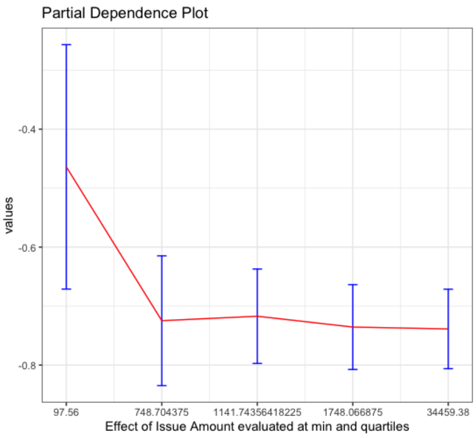
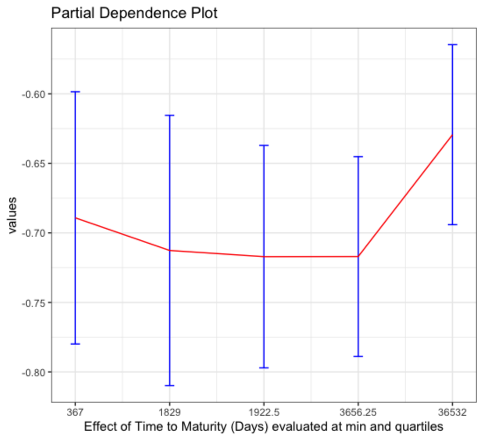


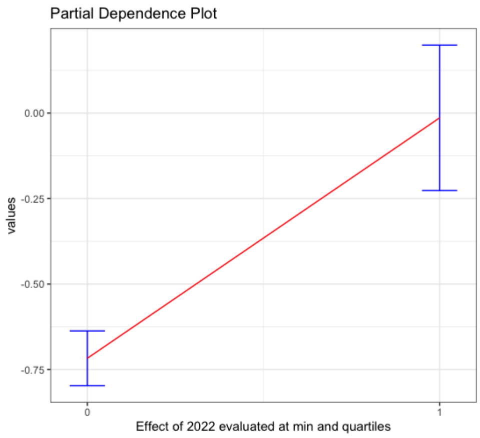

Figure 33: Graph of ATE within Subgroups (Model 6)




(a) Effect of Issue Amount




(b) Effect of Time to Maturity (Days)




(c) Effect of 2022

Figure 34: Partial Dependency Plots (Model 6)

Table 45: Heterogeneity across Covariates (Model 6)

| Variable | Mean ntile1 | Mean ntile2 | Mean ntile3 | Mean ntile4 |
|---|---|---|---|---|
| Time to Maturity (Days) | 2742.93 | 3504.99 | 2683.71 | 1790.09 |
| Issue Amount | 1766.86 | 1622.31 | 1261 | 1734.27 |
| Guarantor | 0.19 | 0.19 | 0.11 | 0.24 |
| 2013 | 0.12 | 0.05 | 0.05 | 0.06 |
| 2014 | 0.11 | 0.06 | 0.06 | 0.05 |
| 2015 | 0.06 | 0.09 | 0.09 | 0.07 |
| 2016 | 0.07 | 0.09 | 0.08 | 0.08 |
| 2017 | 0.02 | 0.1 | 0.11 | 0.06 |
| 2018 | 0.01 | 0.1 | 0.11 | 0.06 |
| 2019 | 0.02 | 0.14 | 0.13 | 0.03 |
| 2020 | 0.01 | 0.08 | 0.09 | 0.07 |
| 2021 | 0.03 | 0.08 | 0.08 | 0.07 |
| 2022 | 0 | 0 | 0 | 0.27 |
| Annual Coupon | 1 | 0.96 | 0.48 | 0.2 |
| Semi Annual Coupon | 0 | 0.04 | 0.51 | 0.8 |
| Quarterly | 0 | 0 | 0 | 0 |
| Senior Secured Mortgage | 0 | 0.19 | 0.14 | 0.05 |
| Senior Secured | 0.03 | 0.08 | 0.03 | 0.07 |
| Senior Unsecured | 0.84 | 0.55 | 0.52 | 0.73 |
| Senior Non Preferred | 0 | 0.02 | 0.09 | 0.02 |
| Senior Preferred | 0 | 0.04 | 0.13 | 0.04 |
| Senior Subordinated Unsecured | 0.01 | 0 | 0 | 0 |
| Subordinated Unsecured | 0.01 | 0.02 | 0.05 | 0 |
| Basic Materials | 0.02 | 0 | 0 | 0 |
| Consumer Cyclicals | 0.02 | 0 | 0 | 0 |
| Consumer Non Cyclicals | 0 | 0 | 0 | 0 |
| Energy | 0.02 | 0 | 0 | 0 |
| Financials | 0.55 | 0.64 | 0.76 | 0.82 |
| Healthcare | 0 | 0 | 0 | 0 |
| Industrials | 0.01 | 0.02 | 0.01 | 0 |
| Institutions, Associations & Organizations | 0.02 | 0.02 | 0.07 | 0.04 |
| Real Estate | 0 | 0.01 | 0 | 0 |
| Technology | 0.02 | 0 | 0 | 0 |
| Utilities | 0.04 | 0.02 | 0.01 | 0 |
| AAA | 0.31 | 0.48 | 0.33 | 0.63 |
| AA | 0.28 | 0.27 | 0.2 | 0.25 |
| A | 0.21 | 0.11 | 0.21 | 0.08 |
| BBB | 0.19 | 0.13 | 0.23 | 0.04 |
| BB | 0.02 | 0 | 0.02 | 0 |
| EUR | 1 | 0.87 | 0.39 | 0.19 |

### C.2.3 PSM Sample

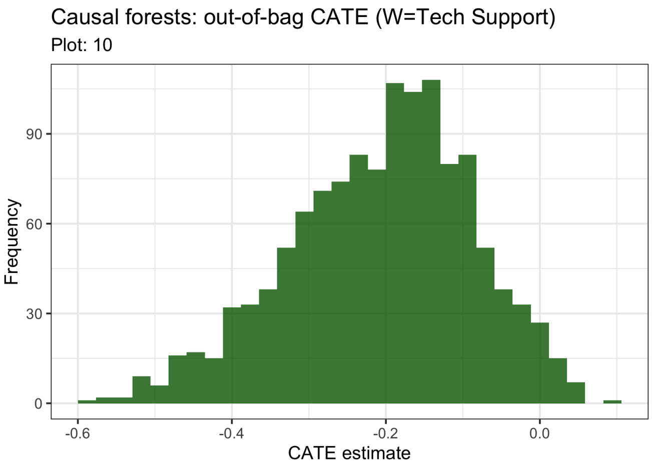



Figure 35: Distribution of CATE (Model 10)

## C.2.3.1 Matching Quality

Table 46: Balance Check for USDEUR Subset

| Variables | Std. Mean Diff. (Pre) | Std. Mean Diff. (Post) | eCDF Max (Pre) | eCDF Max (Post) |
|---|---|---|---|---|
| distance | 0.5507 | 0.2331 | 0.2566 | 0.0994 |
| MTG | -0.1206 | -0.0491 | 0.0306 | 0.0128 |
| SEC | -0.4233 | -0.1202 | 0.0164 | 0.0048 |
| SR | 0.1917 | -0.0142 | 0.0849 | 0.0064 |
| SRBN | 0.1307 | 0.1112 | 0.0311 | 0.0272 |
| SRP | 0.0971 | 0.0468 | 0.0259 | 0.0128 |
| SRSEC | -0.1956 | -0.0394 | 0.0309 | 0.0064 |
| SRSUB | -0.0322 | 0.0000 | 0.0013 | 0.0000 |
| SUB | -0.1733 | 0.0360 | 0.0150 | 0.0032 |
| UN | -0.3018 | -0.0788 | 0.0477 | 0.0128 |
| Time to Maturity (Days) | 0.1856 | 0.0916 | 0.1569 | 0.0593 |
| Guarantor | -0.1357 | -0.0360 | 0.0471 | 0.0128 |
| Euro | 0.1921 | 0.0519 | 0.0890 | 0.0240 |
| U.S. Dollar | -0.1921 | -0.0519 | 0.0890 | 0.0240 |
| A | 0.2108 | 0.0702 | 0.0884 | 0.0288 |
| AA | -0.0967 | -0.0693 | 0.0397 | 0.0288 |
| AAA | -0.3147 | -0.0621 | 0.1458 | 0.0288 |
| B | 0.0131 | 0.0567 | 0.0007 | 0.0032 |
| BB | 0.0040 | -0.0712 | 0.0005 | 0.0080 |
| BBB | 0.2281 | 0.0799 | 0.0959 | 0.03 |

Before Matching: Brown Bonds: 4349, Green Bonds: 663
After Matching: Brown Bonds: 624, Green Bonds 624.

### C.2.3.1 Nuisance Parameter Check

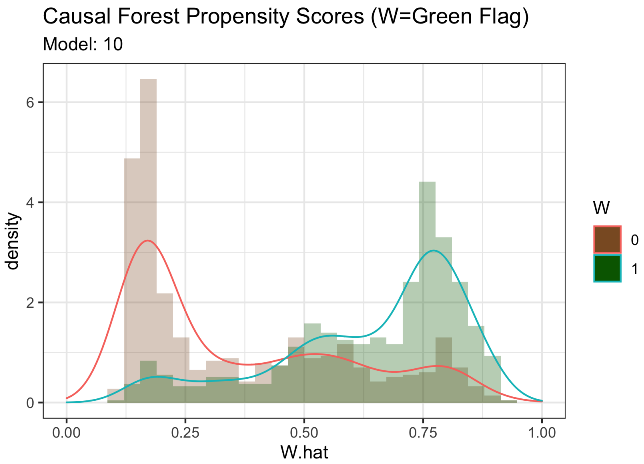



Figure 36: Propensity Score Distribution for Model 10

| | *Dependent variable: Green Flag* |
|---|---|
| e.bar | 1.000*** |
| | (0.024) |
| e.residual | 1.075*** |
| | (0.041) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(a) Outcome Model

| | *Dependent variable: Green Flag* |
|---|---|
| m.bar | 0.999*** |
| | (0.015) |
| m.residual | 1.302*** |
| | (0.031) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(b) Propensity Model

Table 47: Calibration Regressions (Model 10)

#### C.2.3.2 Heterogeneity Assessment

Table 48: Variable Importance (Model 10)

| **Covariate** | **Value** |
|---|---|
| Issue Amount | 0.29489032 |
| Time to Maturity (Days) | 0.21820993 |
| 2022 | 0.05453479 |
| 2020 | 0.04649319 |
| Financials | 0.04166802 |
| 2018 | 0.04093371 |

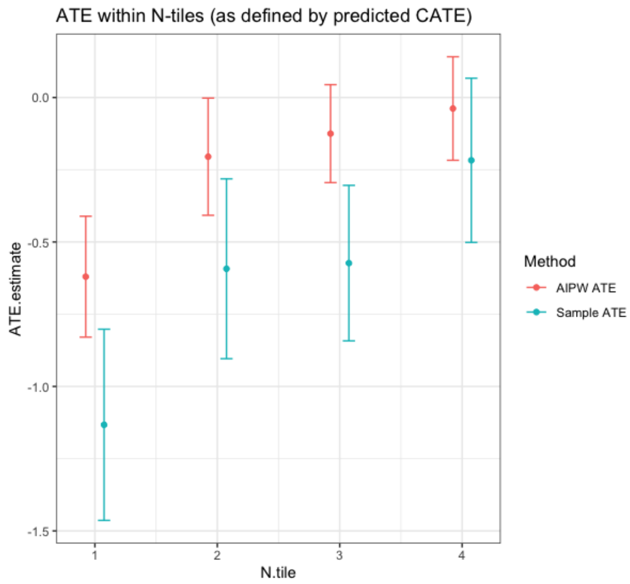
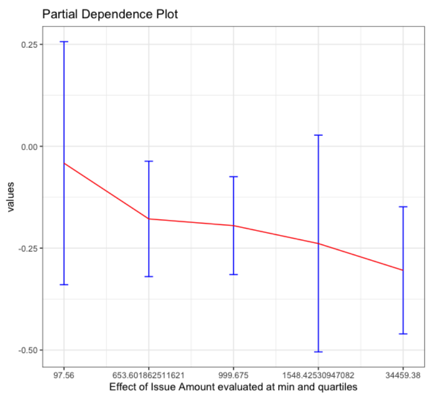
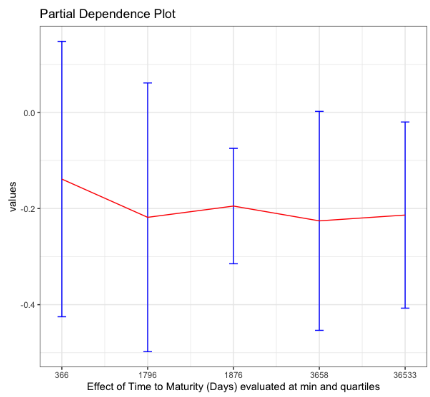


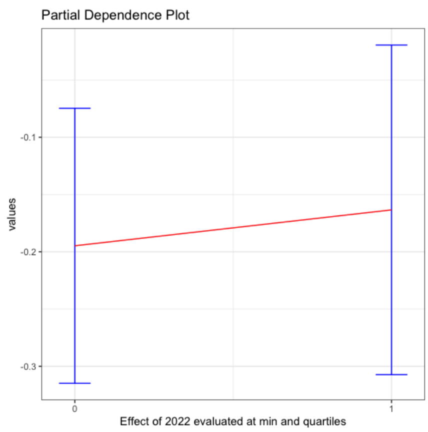

Figure 37: Graph of ATE within Subgroups (Model 10)




(a) Effect of Issue Amount




(b) Effect of Time to Maturity (Days)




(c) Effect of 2022

Figure 38: Partial Dependency Plots (Model 10)

Table 49: Heterogeneity across Covariates (Model 10)

| **Variable** | **Mean ntile1** | **Mean ntile2** | **Mean ntile3** | **Mean ntile4** |
|---|---|---|---|---|
| Time to Maturity (Days) | 3478.94 | 3071.5 | 2698.03 | 2218.26 |
| Issue Amount | 1982.47 | 1664.78 | 1026.88 | 732.29 |
| Guarantor | 0.18 | 0.18 | 0.15 | 0.12 |
| 2013 | 0.08 | 0.03 | 0.03 | 0.03 |
| 2014 | 0.09 | 0.04 | 0.03 | 0.01 |
| 2015 | 0.05 | 0.05 | 0.05 | 0.1 |
| 2016 | 0.09 | 0.06 | 0.06 | 0.08 |
| 2017 | 0.04 | 0.06 | 0.12 | 0.14 |
| 2018 | 0.04 | 0.12 | 0.1 | 0.11 |
| 2019 | 0.08 | 0.14 | 0.15 | 0.09 |
| 2020 | 0.05 | 0.08 | 0.14 | 0.14 |
| 2021 | 0.15 | 0.18 | 0.15 | 0.06 |
| 2022 | 0.08 | 0.12 | 0.1 | 0.19 |
| Annual Coupon | 0.83 | 0.67 | 0.65 | 0.65 |
| Semi Annual Coupon | 0.17 | 0.32 | 0.35 | 0.35 |
| Quarterly | 0 | 0 | 0 | 0 |
| Senior Secured Mortgage | 0.01 | 0.06 | 0.12 | 0.14 |
| Senior Secured | 0.02 | 0.02 | 0.04 | 0.04 |
| Senior Unsecured | 0.91 | 0.75 | 0.62 | 0.59 |
| Senior Non Preferred | 0.01 | 0.05 | 0.08 | 0.06 |
| Senior Preferred | 0.01 | 0.06 | 0.12 | 0.11 |
| Senior Subordinated Unsecured | 0 | 0 | 0 | 0 |
| Subordinated Unsecured | 0 | 0.01 | 0 | 0.01 |
| Basic Materials | 0.04 | 0 | 0.01 | 0.01 |
| Consumer Cyclicals | 0.02 | 0 | 0 | 0 |
| Consumer Non Cyclicals | 0.02 | 0.01 | 0 | 0 |
| Energy | 0.01 | 0 | 0 | 0 |
| Financials | 0.33 | 0.58 | 0.74 | 0.83 |
| Healthcare | 0.01 | 0 | 0 | 0 |
| Industrials | 0.04 | 0.02 | 0.03 | 0.03 |
| Institutions, Associations & Organizations | 0.09 | 0.09 | 0.04 | 0.03 |
| Real Estate | 0.01 | 0 | 0 | 0.01 |
| Technology | 0.02 | 0.01 | 0 | 0 |
| Utilities | 0.09 | 0.04 | 0.04 | 0.02 |
| AAA | 0.32 | 0.39 | 0.34 | 0.27 |
| AA | 0.18 | 0.18 | 0.25 | 0.34 |
| A | 0.18 | 0.18 | 0.22 | 0.22 |
| BBB | 0.29 | 0.24 | 0.16 | 0.17 |
| BB | 0.03 | 0.02 | 0.02 | 0.01 |
| EUR | 0.81 | 0.67 | 0.62 | 0.6 |

# Appendix D: Issuer matched CBI Dataset Analysis

## D.1 Descriptive Statistics

### D.1.1 Summary Statistics

Table 50: Data Matched CBI Green Bond Summary Statistics

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Time to Maturity (Days) | 425 | 2,781.809 | 1,572.795 | 367 | 1,833 | 3,659 | 11,180 |
| Issue Amount | 425 | 1,192.976 | 1,731.084 | 500.000 | 564.302 | 1,120.900 | 17,377.000 |
| Coupon Rate | 425 | 1.257 | 1.142 | 0.000 | 0.375 | 1.875 | 6.125 |
| Guarantor | 425 | 0.169 | 0.376 | 0 | 0 | 0 | 1 |
| Offer Yield to Maturity | 425 | 1.300 | 1.152 | −0.305 | 0.465 | 1.914 | 6.125 |
| Green Flag | 425 | 1.000 | 0.000 | 1 | 1 | 1 | 1 |
| 2008 | 425 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2009 | 425 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2010 | 425 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2011 | 425 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2012 | 425 | 0.002 | 0.049 | 0 | 0 | 0 | 1 |
| 2013 | 425 | 0.019 | 0.136 | 0 | 0 | 0 | 1 |
| 2014 | 425 | 0.019 | 0.136 | 0 | 0 | 0 | 1 |
| 2015 | 425 | 0.054 | 0.227 | 0 | 0 | 0 | 1 |
| 2016 | 425 | 0.073 | 0.260 | 0 | 0 | 0 | 1 |
| 2017 | 425 | 0.096 | 0.296 | 0 | 0 | 0 | 1 |
| 2018 | 425 | 0.106 | 0.308 | 0 | 0 | 0 | 1 |
| 2019 | 425 | 0.169 | 0.376 | 0 | 0 | 0 | 1 |
| 2020 | 425 | 0.120 | 0.325 | 0 | 0 | 0 | 1 |
| 2021 | 425 | 0.186 | 0.389 | 0 | 0 | 0 | 1 |
| 2022 | 425 | 0.155 | 0.363 | 0 | 0 | 0 | 1 |
| AAA | 425 | 0.320 | 0.467 | 0 | 0 | 1 | 1 |
| AA | 425 | 0.193 | 0.395 | 0 | 0 | 0 | 1 |
| A | 425 | 0.231 | 0.422 | 0 | 0 | 0 | 1 |
| BBB | 425 | 0.245 | 0.430 | 0 | 0 | 0 | 1 |
| BB | 425 | 0.012 | 0.108 | 0 | 0 | 0 | 1 |
| B | 425 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| AUD | 425 | 0.007 | 0.084 | 0 | 0 | 0 | 1 |
| BRL | 425 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| CAD | 425 | 0.024 | 0.152 | 0 | 0 | 0 | 1 |
| CLP | 425 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| CNY | 425 | 0.002 | 0.049 | 0 | 0 | 0 | 1 |
| EUR | 425 | 0.666 | 0.472 | 0 | 0 | 1 | 1 |
| GBP | 425 | 0.016 | 0.127 | 0 | 0 | 0 | 1 |
| JPY | 425 | 0.002 | 0.049 | 0 | 0 | 0 | 1 |
| MXN | 425 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| NZD | 425 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| NOK | 425 | 0.002 | 0.049 | 0 | 0 | 0 | 1 |
| SEK | 425 | 0.014 | 0.118 | 0 | 0 | 0 | 1 |
| CHF | 425 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| TRY | 425 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| USD | 425 | 0.266 | 0.442 | 0 | 0 | 1 | 1 |

Table 51: Data Matched CBI Green Bond Summary Statistics cont.

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Annual Coupon | 425 | 0.720 | 0.450 | 0 | 0 | 1 | 1 |
| Semi Annual Coupon | 425 | 0.278 | 0.448 | 0 | 0 | 1 | 1 |
| Quarterly | 425 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| Maturity | 425 | 0.002 | 0.049 | 0 | 0 | 0 | 1 |
| Basic Materials | 425 | 0.007 | 0.084 | 0 | 0 | 0 | 1 |
| Consumer Cyclicals | 425 | 0.007 | 0.084 | 0 | 0 | 0 | 1 |
| Consumer Non-Cyclicals | 425 | 0.007 | 0.084 | 0 | 0 | 0 | 1 |
| Financials | 425 | 0.640 | 0.481 | 0 | 0 | 1 | 1 |
| Government Activity | 425 | 0.160 | 0.367 | 0 | 0 | 0 | 1 |
| Healthcare | 425 | 0.002 | 0.049 | 0 | 0 | 0 | 1 |
| Industrials | 425 | 0.045 | 0.207 | 0 | 0 | 0 | 1 |
| Institutions, Associations & Organizations | 425 | 0.040 | 0.196 | 0 | 0 | 0 | 1 |
| Real Estate | 425 | 0.024 | 0.152 | 0 | 0 | 0 | 1 |
| Technology | 425 | 0.012 | 0.108 | 0 | 0 | 0 | 1 |
| Utilities | 425 | 0.056 | 0.231 | 0 | 0 | 0 | 1 |
| Senior Secured Mortgage | 425 | 0.092 | 0.289 | 0 | 0 | 0 | 1 |
| Senior Secured | 425 | 0.016 | 0.127 | 0 | 0 | 0 | 1 |
| Senior Unsecured | 425 | 0.673 | 0.470 | 0 | 0 | 1 | 1 |
| Senior Non-Preferred | 425 | 0.085 | 0.279 | 0 | 0 | 0 | 1 |
| Senior Preferred | 425 | 0.099 | 0.299 | 0 | 0 | 0 | 1 |
| Senior Subordinated Unsecured | 425 | 0.002 | 0.049 | 0 | 0 | 0 | 1 |
| Subordinated Unsecured | 425 | 0.007 | 0.084 | 0 | 0 | 0 | 1 |
| Unsecured | 425 | 0.024 | 0.152 | 0 | 0 | 0 | 1 |
| Public Sector | 425 | 0.372 | 0.484 | 0 | 0 | 1 | 1 |
| Corporate Sector | 425 | 0.628 | 0.484 | 0 | 0 | 1 | 1 |

Table 52: Data Matched CBI Brown Bond Summary Statistics

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Time to Maturity (Days) | 4,034 | 2,699.585 | 2,545.535 | 373 | 1,743 | 3,485.2 | 36,532 |
| Issue Amount | 4,034 | 1,694.083 | 1,649.116 | 500 | 797.6 | 1,830.8 | 30,089 |
| Coupon Rate | 4,034 | 2.113 | 1.588 | 0.010 | 0.875 | 3.000 | 20.000 |
| Guarantor | 4,034 | 0.185 | 0.388 | 0 | 0 | 0 | 1 |
| Offer Yield to Maturity | 4,034 | 2.143 | 1.590 | 0.003 | 0.914 | 3.040 | 20.000 |
| Green Flag | 4,034 | 0.000 | 0.000 | 0 | 0 | 0 | 0 |
| 2008 | 4,034 | 0.048 | 0.213 | 0 | 0 | 0 | 1 |
| 2009 | 4,034 | 0.053 | 0.224 | 0 | 0 | 0 | 1 |
| 2010 | 4,034 | 0.071 | 0.256 | 0 | 0 | 0 | 1 |
| 2011 | 4,034 | 0.067 | 0.250 | 0 | 0 | 0 | 1 |
| 2012 | 4,034 | 0.087 | 0.282 | 0 | 0 | 0 | 1 |
| 2013 | 4,034 | 0.075 | 0.263 | 0 | 0 | 0 | 1 |
| 2014 | 4,034 | 0.075 | 0.264 | 0 | 0 | 0 | 1 |

Table 53: Data Matched CBI Brown Bond Summary Statistics cont.

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| 2015 | 4,034 | 0.081 | 0.273 | 0 | 0 | 0 | 1 |
| 2016 | 4,034 | 0.083 | 0.276 | 0 | 0 | 0 | 1 |
| 2017 | 4,034 | 0.072 | 0.258 | 0 | 0 | 0 | 1 |
| 2018 | 4,034 | 0.070 | 0.255 | 0 | 0 | 0 | 1 |
| 2019 | 4,034 | 0.075 | 0.263 | 0 | 0 | 0 | 1 |
| 2020 | 4,034 | 0.051 | 0.219 | 0 | 0 | 0 | 1 |
| 2021 | 4,034 | 0.044 | 0.204 | 0 | 0 | 0 | 1 |
| 2022 | 4,034 | 0.049 | 0.217 | 0 | 0 | 0 | 1 |
| AAA | 4,034 | 0.478 | 0.500 | 0 | 0 | 1 | 1 |
| AA | 4,034 | 0.259 | 0.438 | 0 | 0 | 1 | 1 |
| A | 4,034 | 0.136 | 0.343 | 0 | 0 | 0 | 1 |
| BBB | 4,034 | 0.118 | 0.323 | 0 | 0 | 0 | 1 |
| BB | 4,034 | 0.007 | 0.086 | 0 | 0 | 0 | 1 |
| B | 4,034 | 0.001 | 0.035 | 0 | 0 | 0 | 1 |
| AUD | 4,034 | 0.016 | 0.127 | 0 | 0 | 0 | 1 |
| BRL | 4,034 | 0.0002 | 0.016 | 0 | 0 | 0 | 1 |
| CAD | 4,034 | 0.005 | 0.074 | 0 | 0 | 0 | 1 |
| CLP | 4,034 | 0.0005 | 0.022 | 0 | 0 | 0 | 1 |
| CNY | 4,034 | 0.0002 | 0.016 | 0 | 0 | 0 | 1 |
| EUR | 4,034 | 0.525 | 0.499 | 0 | 0 | 1 | 1 |
| GBP | 4,034 | 0.069 | 0.254 | 0 | 0 | 0 | 1 |
| JPY | 4,034 | 0.017 | 0.130 | 0 | 0 | 0 | 1 |
| MXN | 4,034 | 0.0002 | 0.016 | 0 | 0 | 0 | 1 |
| NZD | 4,034 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |
| NOK | 4,034 | 0.0005 | 0.022 | 0 | 0 | 0 | 1 |
| SEK | 4,034 | 0.0002 | 0.016 | 0 | 0 | 0 | 1 |
| CHF | 4,034 | 0.002 | 0.044 | 0 | 0 | 0 | 1 |
| TRY | 4,034 | 0.0002 | 0.016 | 0 | 0 | 0 | 1 |
| USD | 4,034 | 0.362 | 0.481 | 0 | 0 | 1 | 1 |
| Annual Coupon | 4,034 | 0.631 | 0.482 | 0 | 0 | 1 | 1 |
| Semi Annual Coupon | 4,034 | 0.366 | 0.482 | 0 | 0 | 1 | 1 |
| Quarterly | 4,034 | 0.002 | 0.044 | 0 | 0 | 0 | 1 |
| Maturity | 4,034 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |
| Basic Materials | 4,034 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |
| Consumer Cyclicals | 4,034 | 0.005 | 0.074 | 0 | 0 | 0 | 1 |
| Consumer Non-Cyclicals | 4,034 | 0.001 | 0.031 | 0 | 0 | 0 | 1 |
| Financials | 4,034 | 0.716 | 0.451 | 0 | 0 | 1 | 1 |
| Government Activity | 4,034 | 0.208 | 0.406 | 0 | 0 | 0 | 1 |
| Healthcare | 4,034 | 0.0005 | 0.022 | 0 | 0 | 0 | 1 |
| Industrials | 4,034 | 0.007 | 0.082 | 0 | 0 | 0 | 1 |
| Institutions, Associations & Organizations | 4,034 | 0.047 | 0.211 | 0 | 0 | 0 | 1 |
| Real Estate | 4,034 | 0.001 | 0.027 | 0 | 0 | 0 | 1 |
| Technology | 4,034 | 0.004 | 0.061 | 0 | 0 | 0 | 1 |
| Utilities | 4,034 | 0.010 | 0.102 | 0 | 0 | 0 | 1 |
| Senior Secured Mortgage | 4,034 | 0.102 | 0.303 | 0 | 0 | 0 | 1 |
| Senior Secured | 4,034 | 0.059 | 0.236 | 0 | 0 | 0 | 1 |
| Senior Unsecured | 4,034 | 0.627 | 0.484 | 0 | 0 | 1 | 1 |
| Senior Non-Preferred | 4,034 | 0.035 | 0.183 | 0 | 0 | 0 | 1 |
| Senior Preferred | 4,034 | 0.055 | 0.227 | 0 | 0 | 0 | 1 |
| Senior Subordinated Unsecured | 4,034 | 0.003 | 0.054 | 0 | 0 | 0 | 1 |
| Subordinated Unsecured | 4,034 | 0.024 | 0.152 | 0 | 0 | 0 | 1 |
| Unsecured | 4,034 | 0.079 | 0.270 | 0 | 0 | 0 | 1 |
| Public Sector | 4,034 | 0.474 | 0.499 | 0 | 0 | 1 | 1 |
| Corporate Sector | 4,034 | 0.526 | 0.499 | 0 | 0 | 1 | 1 |

### D.1.2 Raincloud Plots

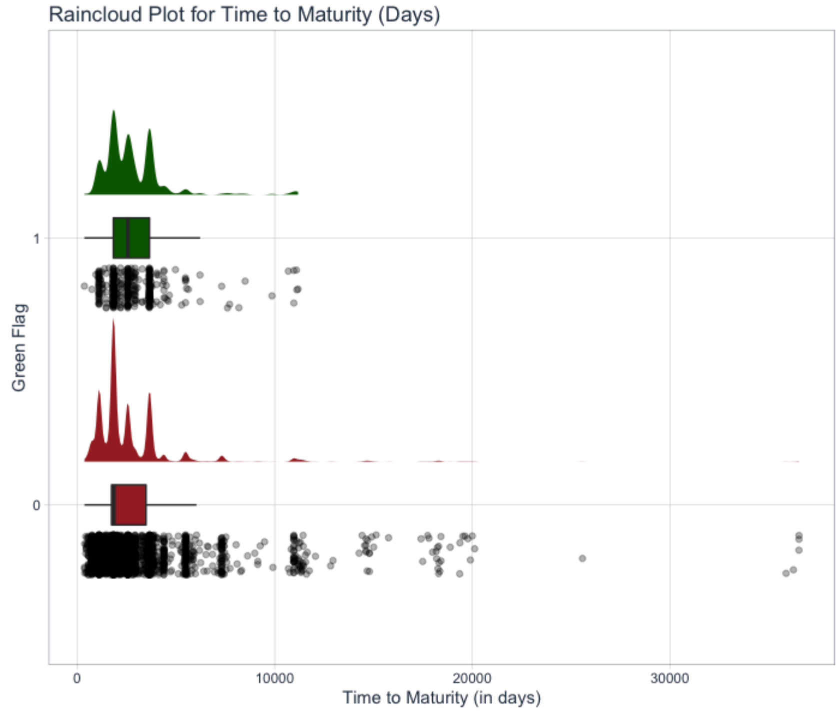



Figure 39: Raincloud Plot for Time to Maturity (Days)

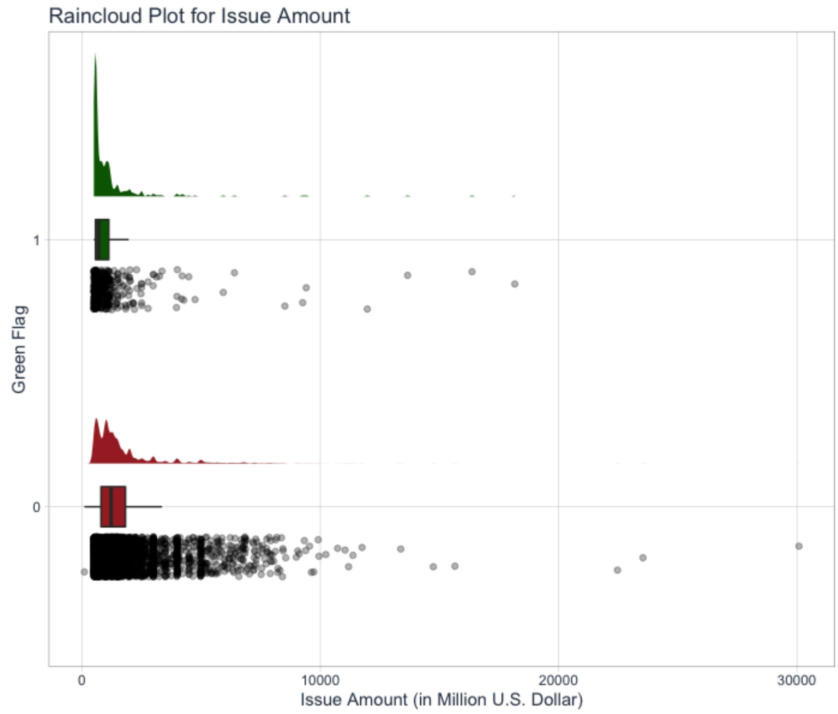



Figure 40: Raincloud for Issue Amount

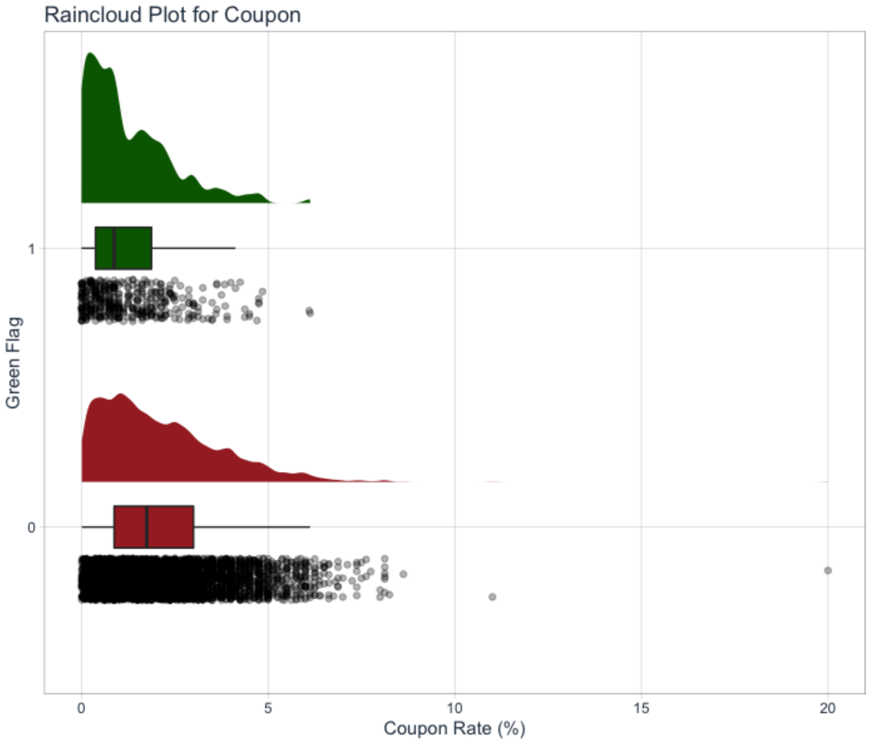



Figure 41: Raincloud for Coupon Rate

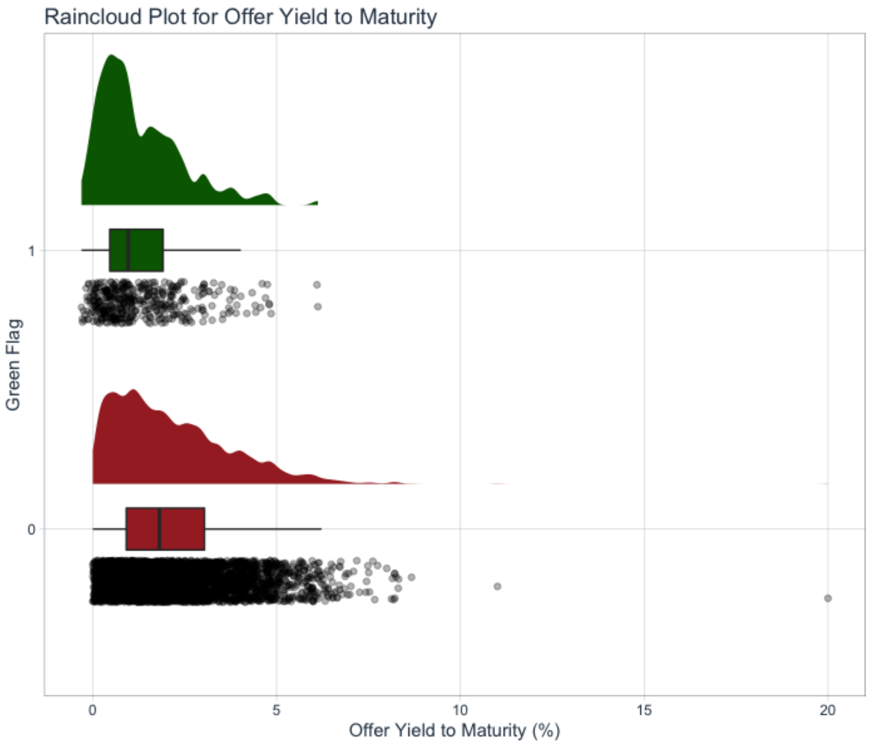



Figure 42: Raincloud for Issuance Yield

### D.1.3 Correlation

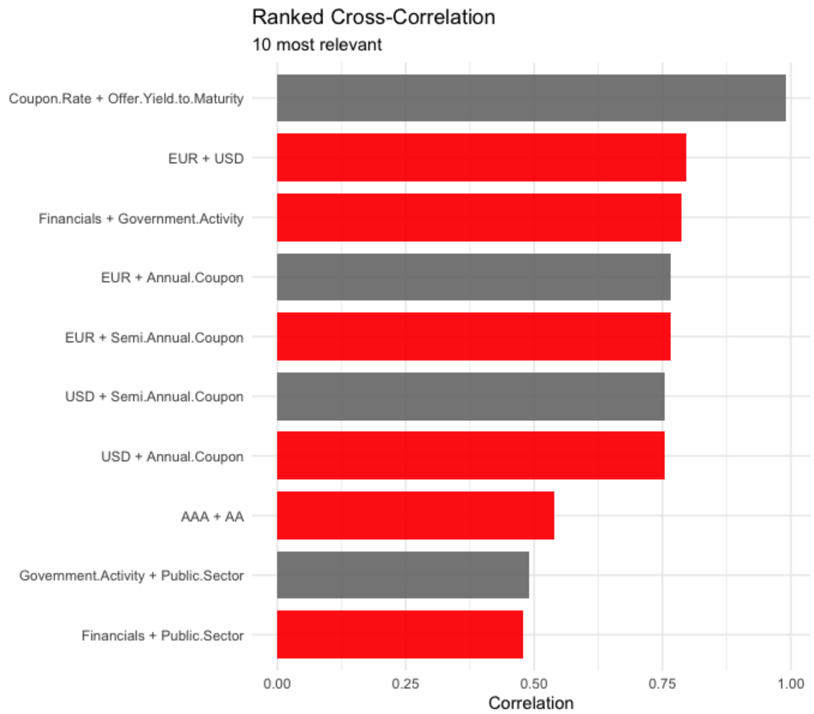



Figure 43: Ranked Cross-Correlation of 10 Most Relevant Pairs

Note: Blue = Positive Correlation, Red = Negative Correlation.

### D.1.4 Propensity Tables

| Issue Year | Green (%) | Brown (%) |
|---|---|---|
| 2008 | 0.0 | 4.8 |
| 2009 | 0.0 | 5.3 |
| 2010 | 0.0 | 7.1 |
| 2011 | 0.0 | 6.7 |
| 2012 | 0.2 | 8.7 |
| 2013 | 1.9 | 7.5 |
| 2014 | 1.9 | 7.5 |
| 2015 | 5.4 | 8.1 |
| 2016 | 7.3 | 8.3 |
| 2017 | 9.6 | 7.2 |
| 2018 | 10.6 | 7.0 |
| 2019 | 16.9 | 7.5 |
| 2020 | 12.0 | 5.1 |
| 2021 | 18.6 | 4.4 |
| 2022 | 15.5 | 4.9 |

(a) Issue Year

| Rating | Green (%) | Brown (%) |
|---|---|---|
| AAA | 32.0 | 47.8 |
| AA | 19.3 | 25.9 |
| A | 23.1 | 13.6 |
| BBB | 24.5 | 11.8 |
| BB | 1.2 | 0.7 |
| B | 0.0 | 0.1 |
| CCC | 0.0 | 0.0 |

(b) Rating

Table 54: Propensity Tables

Table 55: Propensity Table for Coupon Frequency

| Coupon Frequency | Green (%) | Brown (%) |
|---|---|---|
| Annual Coupon | 71.6 | 65.2 |
| Semi Annual Coupon | 28.2 | 34.6 |
| Quarterly | 0.0 | 0.2 |
| Maturity | 0.2 | 0.1 |

Table 56: Propensity Table for Industry

| | | |
|---|---|---|
| Academic & Educational Services | 0.0 | 0.0 |
| Basic Materials | 0.7 | 0.1 |
| Consumer Cyclicals | 0.7 | 0.5 |
| Consumer Non-Cyclicals | 0.7 | 0.1 |
| Energy | 0.0 | 0.0 |
| Financials | 64.0 | 71.6 |
| Government Activity | 16.0 | 20.8 |
| Healthcare | 0.2 | 0.0 |
| Industrials | 4.5 | 0.7 |
| Institutions, Associations & Organizations | 4.0 | 4.7 |
| Real Estate | 2.4 | 0.1 |
| Technology | 1.2 | 0.4 |
| Utilities | 5.6 | 1.0 |

Table 57: Propensity Table for Currency

| Currency | Green (%) | Brown (%) |
|---|---|---|
| AUD | 0.7 | 1.6 |
| BRL | 0.0 | 0.0 |
| CAD | 2.4 | 0.5 |
| CLP | 0.0 | 0.0 |
| CNY | 0.2 | 0.0 |
| COP | 0.0 | 0.0 |
| HRK | 0.0 | 0.0 |
| EUR | 66.6 | 52.5 |
| GBP | 1.6 | 6.9 |
| HKD | 0.0 | 0.0 |
| JPY | 0.2 | 1.7 |
| KZT | 0.0 | 0.0 |
| MXN | 0.0 | 0.0 |
| NZD | 0.0 | 0.1 |
| NOK | 0.2 | 0.0 |
| PEN | 0.0 | 0.0 |
| PHP | 0.0 | 0.0 |
| RUB | 0.0 | 0.0 |
| SGD | 0.0 | 0.0 |
| SEK | 1.4 | 0.0 |
| CHF | 0.0 | 0.2 |
| THB | 0.0 | 0.0 |
| TRY | 0.0 | 0.0 |
| USD | 26.6 | 36.2 |
| UYU | 0.0 | 0.0 |

Table 58: Propensity Table for Seniority

| Seniority | Green (%) | Brown (%) |
|---|---|---|
| First-Lien Loan | 0.0 | 0.0 |
| First Mortgage | 0.0 | 0.0 |
| First Refunding Mortgage | 0.0 | 0.0 |
| Second-Lien Loan | 0.0 | 0.0 |
| Junior Subordinated | 0.0 | 0.0 |
| Senior Secured Mortgage | 9.2 | 10.2 |
| Refunding Mortgage | 0.0 | 0.0 |
| Senior Secured | 67.3 | 62.7 |
| Senior Unsecured | 8.5 | 3.5 |
| Senior Non-Preferred | 9.9 | 5.5 |
| Senior Preferred | 1.6 | 5.9 |
| Senior Subordinated Unsecured | 0.2 | 0.3 |
| Senior Subordinated Secured | 0.0 | 0.0 |
| Subordinated Unsecured | 0.7 | 2.4 |
| Subordinated Secured | 0.0 | 0.0 |
| Unsecured | 2.4 | 7.9 |

| Issuer Sector | Green (%) | Brown (%) |
|---|---|---|
| Public Sector | 52.6 | 62.8 |
| Corporate Sector | 47.4 | 37.2 |

(a) Issuer Sector

| Guarantor | Green (%) | Brown (%) |
|---|---|---|
| Guarantor | 16.9 | 18.5 |
| No Guarantor | 83.1 | 81.5 |

(b) Guarantor

Table 59: Propensity Table for Issuer Sector and Guarantor

## D.2 Causal Forest

### D.2.1 Without Issuer Controls

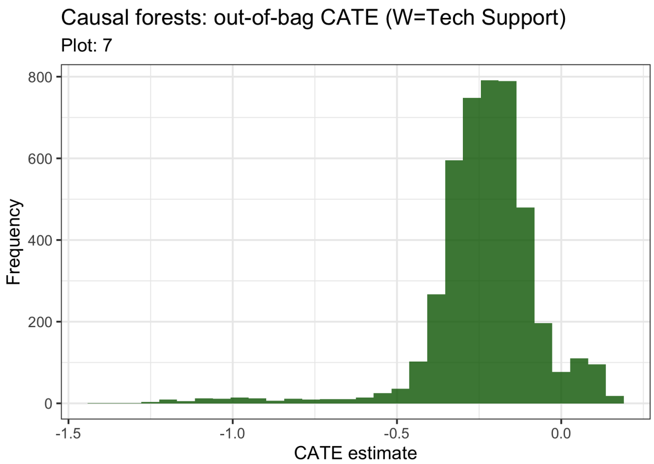



Figure 44: Distribution of CATE (Model 7)

#### D.2.1.1 Nuisance Parameter Check

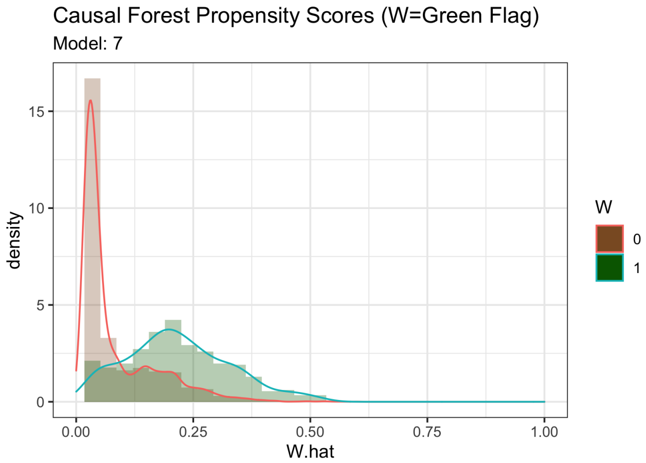



Figure 45: Propensity Score Distribution (Model 7)

| | *Dependent variable: Green Flag* |
|---|---|
| e.bar | 1.006*** |
| | (0.042) |
| e.residual | 1.323*** |
| | (0.066) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(a) Outcome Model

| | *Dependent variable: Green Flag* |
|---|---|
| m.bar | 0.999*** |
| | (0.013) |
| m.residual | 1.290*** |
| | (0.020) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(b) Propensity Model

Table 60: Calibration Regressions (Model 7)

#### D.2.1.2 Heterogeneity Assessment

Table 61: Variable Importance (Model 7)

| **Covariate** | **Value** |
|---|---|
| Issue Amount | 0.25784685 |
| 2022 | 0.21632832 |
| Time to Maturity (Days) | 0.13669900 |
| 2021 | 0.06129829 |
| 2017 | 0.04908605 |
| 2020 | 0.03483198 |

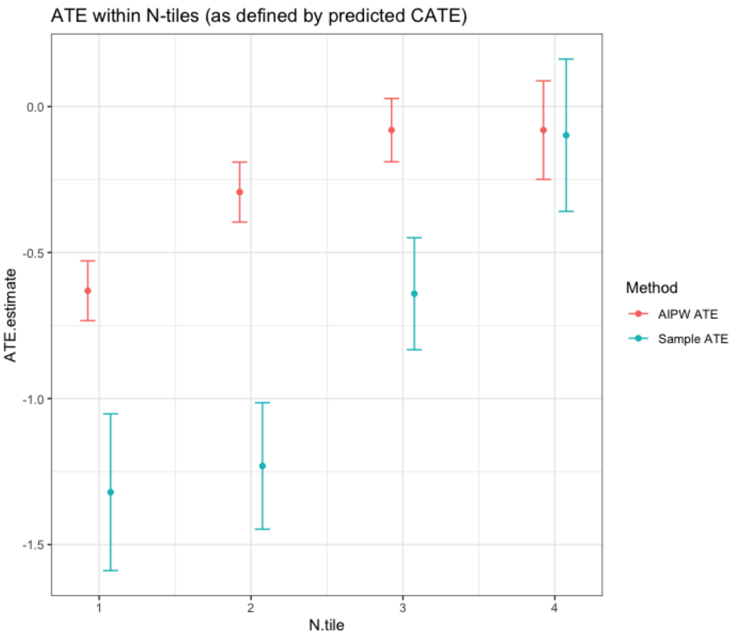
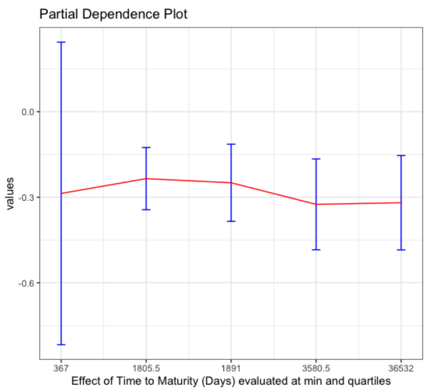
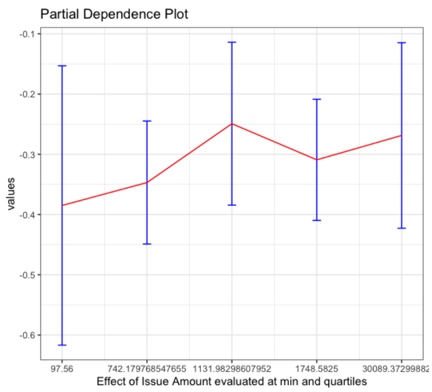


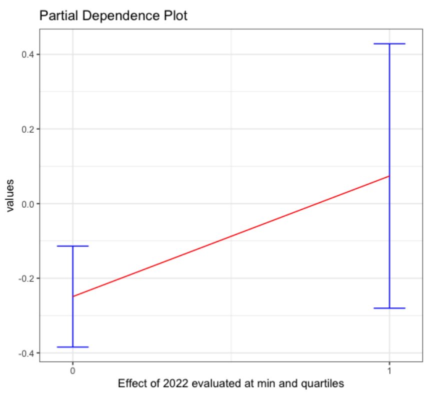

Figure 46: Graph of ATE within Subgroups (Model 7)




(a) Effect of Time to Maturity (Days)




(b) Effect of Issue Amount




(c) Effect of 2022

Figure 47: Partial Dependency Plots (Model 7)

Table 62: Heterogeneity across Covariates (Model 7)

| Variable | Mean ntile1 | Mean ntile2 | Mean ntile3 | Mean ntile4 |
|---|---|---|---|---|
| Time to Maturity (Days) | 3473.98 | 2953.37 | 2266.62 | 2135.21 |
| Issue Amount | 1421.98 | 1658.54 | 1604.77 | 1885.93 |
| Guarantor | 0.12 | 0.19 | 0.18 | 0.25 |
| 2013 | 0.09 | 0.09 | 0.06 | 0.04 |
| 2014 | 0.11 | 0.08 | 0.05 | 0.03 |
| 2015 | 0.1 | 0.11 | 0.07 | 0.04 |
| 2016 | 0.1 | 0.1 | 0.06 | 0.06 |
| 2017 | 0 | 0.02 | 0.06 | 0.22 |
| 2018 | 0.01 | 0.05 | 0.12 | 0.11 |
| 2019 | 0.11 | 0.1 | 0.11 | 0.02 |
| 2020 | 0.01 | 0.04 | 0.09 | 0.09 |
| 2021 | 0 | 0.06 | 0.15 | 0.02 |
| 2022 | 0 | 0 | 0 | 0.24 |
| Annual Coupon | 0.85 | 0.76 | 0.56 | 0.39 |
| Semi Annual Coupon | 0.15 | 0.24 | 0.44 | 0.6 |
| Quarterly | 0 | 0 | 0 | 0 |
| Senior Secured Mortgage | 0.13 | 0.12 | 0.08 | 0.08 |
| Senior Secured | 0.07 | 0.06 | 0.04 | 0.05 |
| Senior Unsecured | 0.66 | 0.6 | 0.59 | 0.68 |
| Senior Non Preferred | 0 | 0.01 | 0.07 | 0.07 |
| Senior Preferred | 0.02 | 0.03 | 0.1 | 0.08 |
| Senior Subordinated Unsecured | 0.01 | 0 | 0 | 0 |
| Subordinated Unsecured | 0.03 | 0.04 | 0.01 | 0 |
| Basic Materials | 0 | 0 | 0 | 0 |
| Consumer Cyclicals | 0.01 | 0 | 0 | 0 |
| Consumer Non Cyclicals | 0 | 0 | 0 | 0 |
| Financials | 0.68 | 0.67 | 0.74 | 0.75 |
| Healthcare | 0 | 0 | 0 | 0 |
| Industrials | 0.02 | 0.01 | 0.01 | 0.01 |
| Institutions, Associations & Organizations | 0.05 | 0.03 | 0.07 | 0.03 |
| Real Estate | 0.01 | 0 | 0 | 0 |
| Technology | 0.01 | 0.01 | 0 | 0 |
| Utilities | 0.04 | 0.01 | 0 | 0 |
| AAA | 0.49 | 0.48 | 0.45 | 0.44 |
| AA | 0.24 | 0.23 | 0.24 | 0.31 |
| A | 0.16 | 0.15 | 0.16 | 0.11 |
| BBB | 0.1 | 0.13 | 0.15 | 0.13 |
| BB | 0.01 | 0.01 | 0.01 | 0.01 |
| AUD | 0.03 | 0.01 | 0.02 | 0.01 |
| CAD | 0 | 0 | 0.01 | 0.01 |
| CLP | 0 | 0 | 0 | 0 |
| CNY | 0 | 0 | 0 | 0 |
| EUR | 0.73 | 0.63 | 0.46 | 0.33 |
| GBP | 0.08 | 0.09 | 0.05 | 0.04 |
| JPY | 0.01 | 0.02 | 0.02 | 0.01 |
| NZD | 0 | 0 | 0 | 0 |
| NOK | 0 | 0 | 0 | 0 |
| SEK | 0 | 0 | 0 | 0 |

### D.2.2 With Issuer Controls

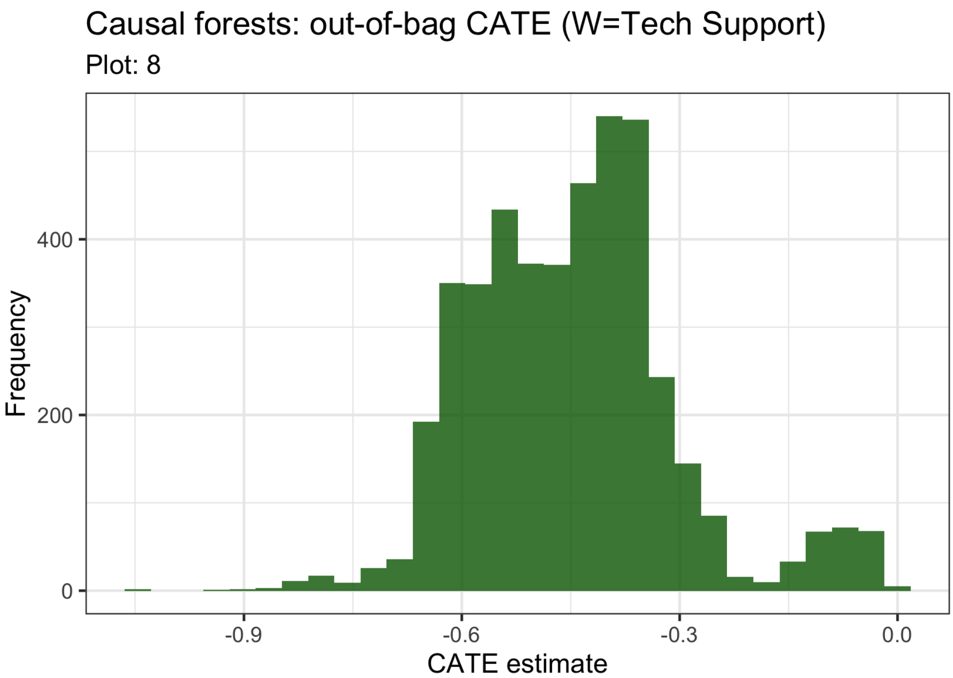



Figure 48: Distribution of CATE (Model 8)

#### D.2.2.1 Nuisance Parameter Check

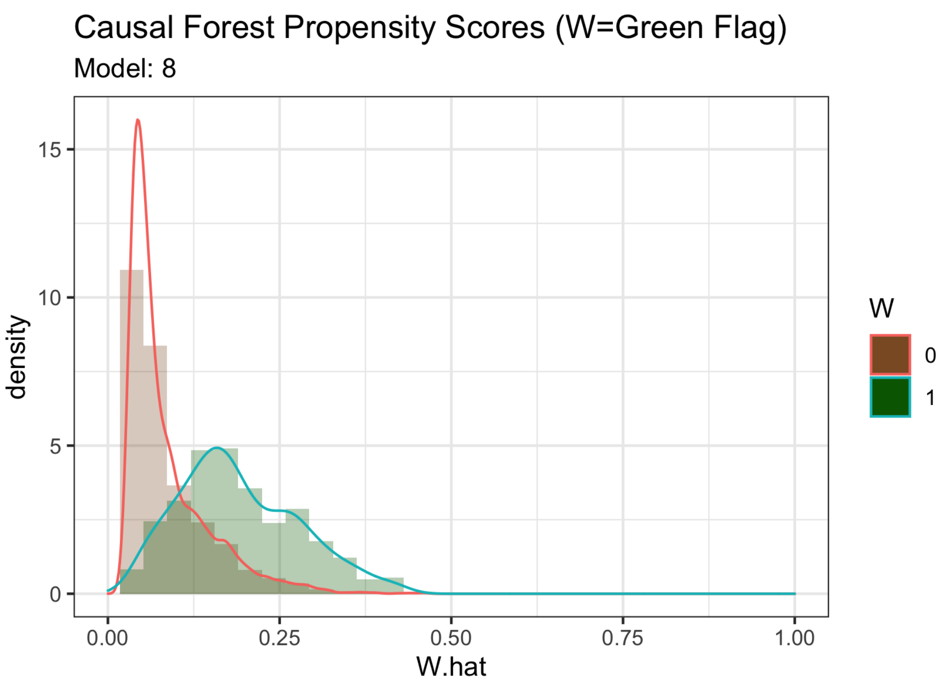



Figure 49: Propensity Score Distribution (Model 8)

| | *Dependent variable: Green Flag* |
|---|---|
| e.bar | 1.004*** |
| | (0.042) |
| e.residual | 1.863*** |
| | (0.089) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(a) Outcome Model

| | *Dependent variable: Green Flag* |
|---|---|
| m.bar | 1.000*** |
| | (0.013) |
| m.residual | 1.863*** |
| | (0.030) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(b) Propensity Model

Table 63: Calibration Regressions (Model 8)

#### D.2.2.2 Heterogeneity Assessment

Table 64: Variable Importance (Model 8)

| Covariate | Value |
|---|---|
| Issue Amount | 0.11442882 |
| 2022 | 0.10675800 |
| Time to Maturity (Days) | 0.10417361 |
| 2017 | 0.05447359 |
| 2018 | 0.04843323 |
| Senior Preferred | 0.04269503 |

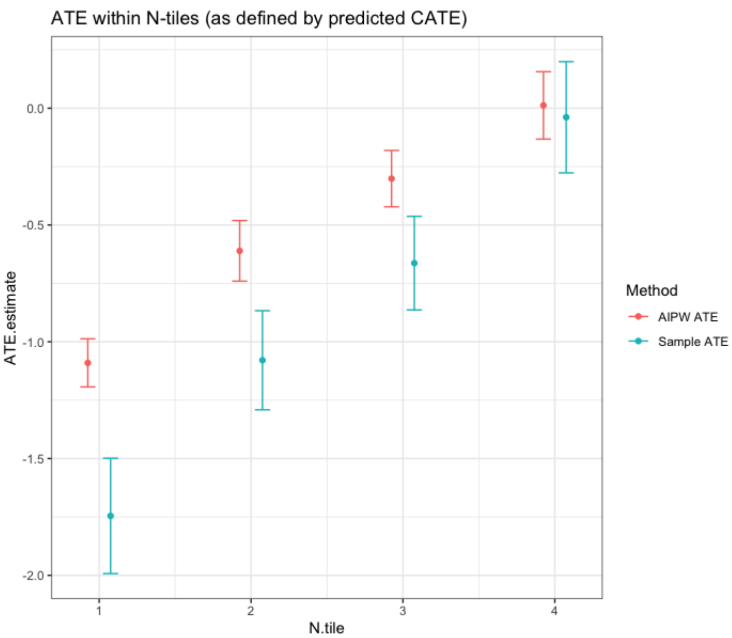
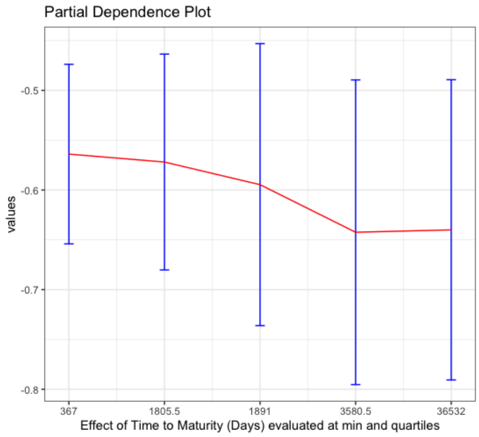
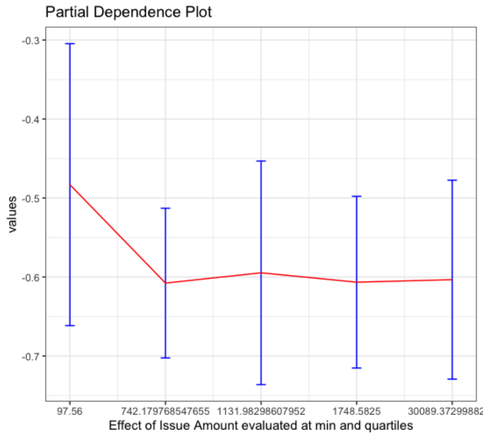


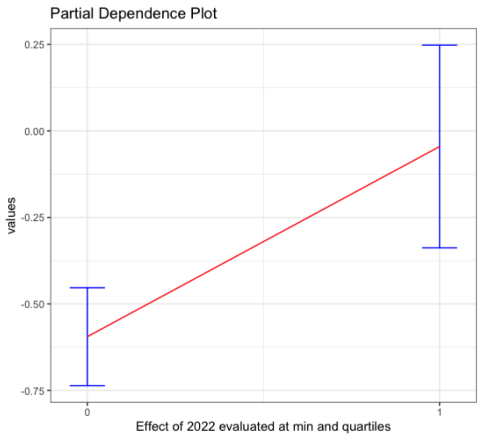

Figure 50: Graph of ATE within Subgroups (Model 8)




(a) Effect of Time to Maturity (Days)




(b) Effect of Issue Amount




(c) Effect of 2022

Figure 51: Partial Dependency Plots (Model 8)

Table 65: Heterogeneity across Covariates (Model 8)

| Variable | Mean ntile1 | Mean ntile2 | Mean ntile3 | Mean ntile4 |
|---|---|---|---|---|
| Time to Maturity (Days) | 3303.11 | 3224.23 | 2350.64 | 1951.02 |
| Issue Amount | 1768.42 | 1566.89 | 1679.22 | 1556.38 |
| Guarantor | 0.15 | 0.2 | 0.18 | 0.2 |
| 2013 | 0.12 | 0.06 | 0.08 | 0.02 |
| 2014 | 0.11 | 0.08 | 0.06 | 0.02 |
| 2015 | 0.06 | 0.11 | 0.08 | 0.06 |
| 2016 | 0.09 | 0.1 | 0.07 | 0.08 |
| 2017 | 0 | 0.01 | 0.1 | 0.19 |
| 2018 | 0 | 0.04 | 0.09 | 0.16 |
| 2019 | 0.04 | 0.15 | 0.1 | 0.05 |
| 2020 | 0.01 | 0.07 | 0.07 | 0.08 |
| 2021 | 0.01 | 0.09 | 0.1 | 0.02 |
| 2022 | 0 | 0 | 0 | 0.24 |
| Annual Coupon | 0.99 | 0.78 | 0.38 | 0.41 |
| Semi Annual Coupon | 0.01 | 0.21 | 0.62 | 0.59 |
| Quarterly | 0 | 0 | 0 | 0 |
| Senior Secured Mortgage | 0.02 | 0.19 | 0.07 | 0.11 |
| Senior Secured | 0.05 | 0.07 | 0.05 | 0.04 |
| Senior Unsecured | 0.82 | 0.52 | 0.63 | 0.56 |
| Senior Non Preferred | 0 | 0 | 0.04 | 0.11 |
| Senior Preferred | 0 | 0.03 | 0.08 | 0.13 |
| Senior Subordinated Unsecured | 0.01 | 0 | 0 | 0 |
| Subordinated Unsecured | 0.02 | 0.04 | 0.02 | 0 |
| Basic Materials | 0 | 0 | 0 | 0 |
| Consumer Cyclicals | 0.02 | 0 | 0 | 0 |
| Consumer Non Cyclicals | 0 | 0.01 | 0 | 0 |
| Financials | 0.65 | 0.65 | 0.74 | 0.79 |
| Healthcare | 0 | 0 | 0 | 0 |
| Industrials | 0.02 | 0.01 | 0.01 | 0.01 |
| Institutions, Associations & Organizations | 0.04 | 0.03 | 0.08 | 0.04 |
| Real Estate | 0 | 0.01 | 0 | 0 |
| Technology | 0.01 | 0.01 | 0 | 0 |
| Utilities | 0.04 | 0.01 | 0 | 0 |
| AAA | 0.42 | 0.51 | 0.5 | 0.42 |
| AA | 0.25 | 0.23 | 0.22 | 0.31 |
| A | 0.18 | 0.12 | 0.16 | 0.12 |
| BBB | 0.13 | 0.14 | 0.12 | 0.14 |
| BB | 0.01 | 0.01 | 0 | 0.01 |
| AUD | 0.01 | 0.02 | 0.03 | 0.01 |
| CAD | 0 | 0 | 0.01 | 0.01 |
| CLP | 0 | 0 | 0 | 0 |
| CNY | 0 | 0 | 0 | 0 |
| EUR | 0.86 | 0.61 | 0.32 | 0.36 |
| GBP | 0.06 | 0.11 | 0.04 | 0.04 |
| JPY | 0 | 0.01 | 0.03 | 0.02 |
| NZD | 0 | 0 | 0 | 0 |
| NOK | 0 | 0 | 0 | 0 |
| SEK | 0 | 0 | 0 | 0 |

### D.2.3 PSM Sample

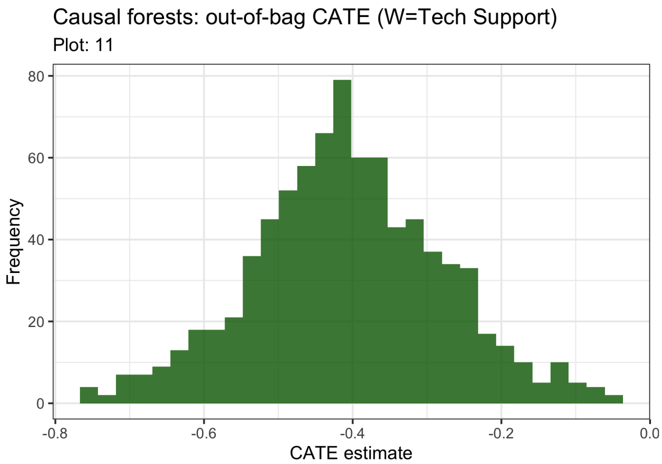



Figure 52: Distribution of CATE (Model 11)

#### D.2.3.1 Matching Quality

Table 66: Balance Check for CBI subset

| | Std. Mean Diff. (Pre) | Std. Mean Diff. (Post) | eCDF Max (Pre) | eCDF Max (Post) |
|---|---|---|---|---|
| distance | 0.5256 | 0.3648 | 0.3347 | 0.1474 |
| MTG | -0.0359 | -0.0417 | 0.0104 | 0.0123 |
| SEC | -0.3045 | -0.1985 | 0.0148 | 0.0098 |
| SR | 0.0981 | 0.0155 | 0.0460 | 0.0074 |
| SRBN | 0.1796 | 0.1298 | 0.0500 | 0.0369 |
| SRP | 0.1484 | 0.0646 | 0.0443 | 0.0197 |
| SRSEC | -0.3341 | -0.0945 | 0.0425 | 0.0123 |
| SRSUB | -0.0128 | 0.0000 | 0.0006 | 0.0000 |
| SUB | -0.1970 | 0.0287 | 0.0165 | 0.0025 |
| UN | -0.3665 | -0.2063 | 0.0555 | 0.0319 |
| Time to Maturity (Days) | 0.0523 | 0.0135 | 0.1602 | 0.0811 |
| Guarantor | -0.0420 | 0.0386 | 0.0158 | 0.0147 |
| Australian Dollar | -0.1111 | 0.0000 | 0.0093 | 0.0000 |
| Canadian Dollar | 0.1193 | 0.0635 | 0.0181 | 0.0098 |
| Chilian Peso | -0.0234 | -0.0701 | 0.0005 | 0.0025 |
| Chinese Yuan Renminbi | 0.0434 | 0.0496 | 0.0021 | 0.0025 |
| Euro | 0.2991 | -0.0208 | 0.1411 | 0.0098 |
| Great Britain Pound | -0.4140 | -0.0189 | 0.0527 | 0.0025 |
| Japanese Yen | -0.3045 | -0.0496 | 0.0148 | 0.0025 |
| Mexican Peso | -0.0166 | -0.0701 | 0.0002 | 0.0025 |
| Norwegian Krone | 0.0383 | 0.0000 | 0.0019 | 0.0000 |
| Swedish Krona | 0.1176 | 0.1019 | 0.0139 | 0.0123 |
| Swiss Franc | -0.0469 | -0.0701 | 0.0020 | 0.0025 |
| U.S. Dollar | -0.2174 | -0.0055 | 0.0960 | 0.0025 |
| A | 0.2243 | 0.0354 | 0.0945 | 0.0147 |
| AA | -0.1675 | -0.0309 | 0.0661 | 0.0123 |
| AAA | -0.3391 | -0.0781 | 0.1582 | 0.0369 |
| BB | 0.0401 | 0.0000 | 0.0043 | 0.0000 |
| BBB | 0.2947 | 0.0810 | 0.1267 | 0.0344 |

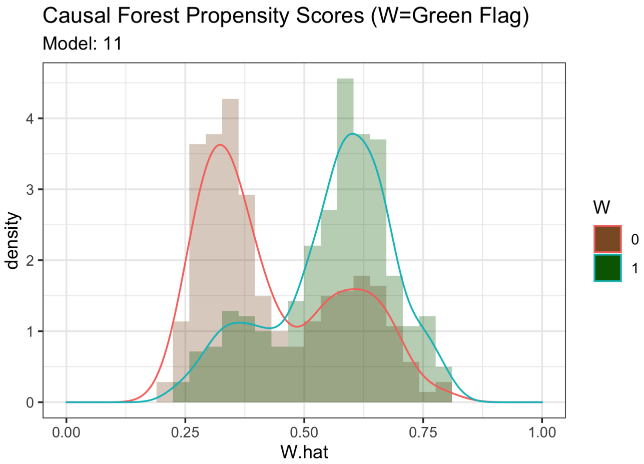



Figure 53: Propensity Score Distribution (Model 11)

#### D.2.3.1 Nuisance Parameter Check

| | *Dependent variable: Green Flag* |
|---|---|
| e.bar | 1.007*** |
| | (0.032) |
| e.residual | 1.403*** |
| | (0.100) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(a) Outcome Model

| | *Dependent variable: Green Flag* |
|---|---|
| m.bar | 0.993*** |
| | (0.022) |
| m.residual | 1.352*** |
| | (0.046) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

(b) Propensity Model

Table 67: Calibration Regressions (Model 11)

#### D.2.3.2 Heterogeneity Assessment

Table 68: Variable Importance (Model 11)

| **Covariate** | **Value** |
|---|---|
| Issue Amount | 0.27828264 |
| Time to Maturity (Days) | 0.21126808 |
| 2022 | 0.06773554 |
| 2017 | 0.05889331 |
| Financials | 0.03908237 |
| 2018 | 0.03796538 |

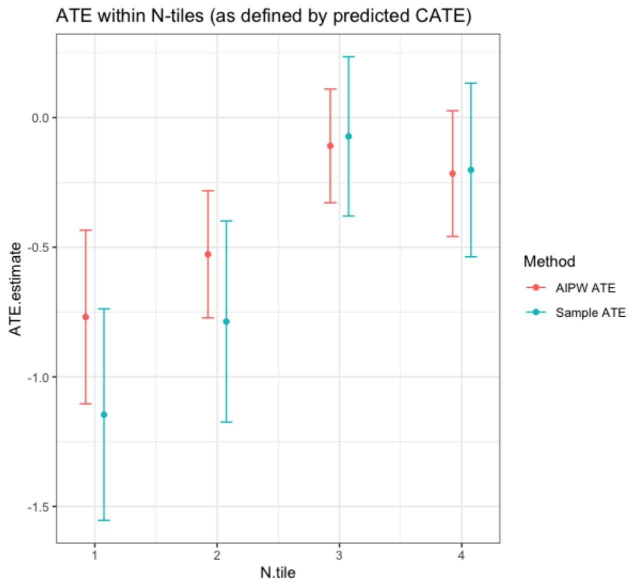
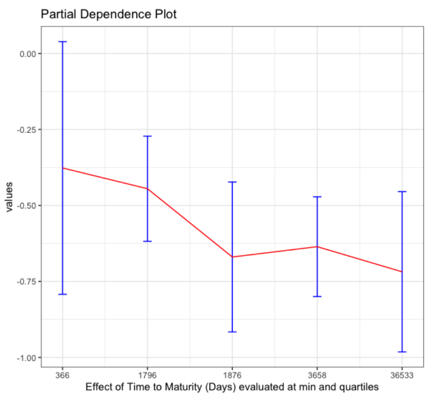
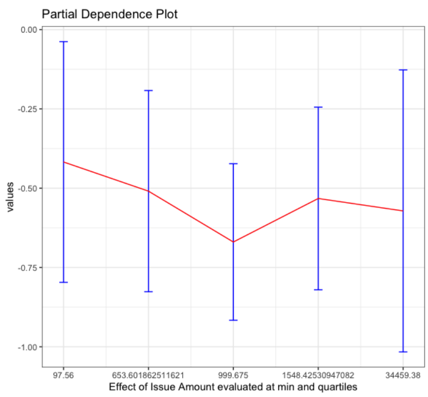


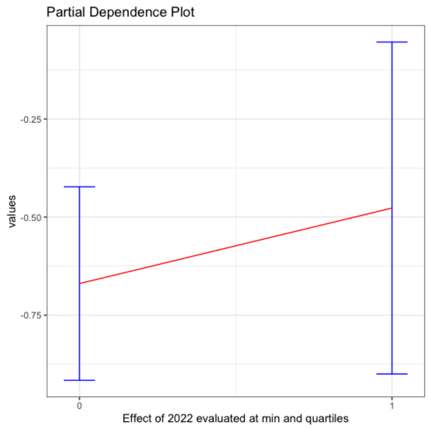

Figure 54: Graph of ATE within Subgroups (Model 11)




(a) Effect of Time to Maturity (Days)




(b) Effect of Issue Amount




(c) Effect of 2022

Figure 55: Partial Dependency Plots (Model 11)

Table 69: Heterogeneity across Covariates (Model 11)

| Variable | Mean ntile1 | Mean ntile2 | Mean ntile3 | Mean ntile4 |
|---|---|---|---|---|
| Time to Maturity (Days) | 2931.14 | 2871.15 | 2867.21 | 2227.99 |
| Issue Amount | 1439.89 | 1413.98 | 1346.45 | 730.88 |
| Guarantor | 0.19 | 0.22 | 0.2 | 0.08 |
| 2013 | 0.1 | 0.05 | 0.02 | 0.01 |
| 2014 | 0.1 | 0.04 | 0.02 | 0 |
| 2015 | 0.05 | 0.08 | 0.08 | 0.07 |
| 2016 | 0.08 | 0.11 | 0.1 | 0.05 |
| 2017 | 0 | 0 | 0.1 | 0.29 |
| 2018 | 0 | 0.04 | 0.15 | 0.2 |
| 2019 | 0.11 | 0.17 | 0.13 | 0.13 |
| 2020 | 0.11 | 0.09 | 0.08 | 0.03 |
| 2021 | 0.17 | 0.15 | 0.12 | 0.02 |
| 2022 | 0 | 0.11 | 0.14 | 0.19 |
| Annual Coupon | 0.75 | 0.63 | 0.65 | 0.84 |
| Semi Annual Coupon | 0.25 | 0.37 | 0.35 | 0.16 |
| Quarterly | 0 | 0 | 0 | 0 |
| Senior Secured Mortgage | 0.08 | 0.1 | 0.08 | 0.15 |
| Senior Secured | 0.03 | 0.01 | 0.03 | 0.02 |
| Senior Unsecured | 0.78 | 0.72 | 0.67 | 0.45 |
| Senior Non Preferred | 0.01 | 0.06 | 0.09 | 0.11 |
| Senior Preferred | 0 | 0.05 | 0.08 | 0.24 |
| Senior Subordinated Unsecured | 0 | 0 | 0 | 0 |
| Subordinated Unsecured | 0.01 | 0 | 0.01 | 0 |
| Basic Materials | 0 | 0.02 | 0 | 0 |
| Consumer Cyclicals | 0.01 | 0.01 | 0 | 0 |
| Consumer Non Cyclicals | 0.01 | 0.02 | 0 | 0 |
| Financials | 0.55 | 0.58 | 0.67 | 0.86 |
| Healthcare | 0 | 0 | 0 | 0 |
| Industrials | 0.04 | 0.03 | 0.04 | 0.03 |
| Institutions, Associations & Organizations | 0.04 | 0.06 | 0.04 | 0.02 |
| Real Estate | 0 | 0.02 | 0 | 0 |
| Technology | 0.01 | 0.01 | 0 | 0 |
| Utilities | 0.09 | 0.04 | 0.05 | 0.01 |
| AAA | 0.43 | 0.37 | 0.35 | 0.26 |
| AA | 0.13 | 0.2 | 0.21 | 0.28 |
| A | 0.19 | 0.21 | 0.18 | 0.28 |
| BBB | 0.24 | 0.21 | 0.25 | 0.19 |
| BB | 0.01 | 0.02 | 0.01 | 0 |
| AUD | 0 | 0 | 0.01 | 0 |
| CAD | 0.02 | 0.03 | 0.02 | 0.01 |
| CLP | 0 | 0 | 0 | 0 |
| CNY | 0 | 0 | 0 | 0 |
| EUR | 0.67 | 0.57 | 0.6 | 0.82 |
| GBP | 0.04 | 0.02 | 0.01 | 0 |
| JPY | 0.01 | 0 | 0 | 0 |
| NZD | 0 | 0 | 0 | 0 |
| NOK | 0 | 0 | 0 | 0 |
| SEK | 0.02 | 0 | 0 | 0 |

Table 70: List of ISINs: Bloomberg Added Data

| **ISINs** | |
|---|---|
| ES0200002063 | XS2355599353 |
| DE0001030724 | XS2356033147 |
| DE000A1KRJV6 | XS2366741770 |
| DE000BHY0GD1 | XS2376820259 |
| DE000GRN0024 | XS2380748439 |
| DE000BHY0GE9 | XS2382267750 |
| DE000BHY0GX9 | XS2382951148 |
| DE000HV2AYN4 | XS2388457264 |
| DE000NLB3UX1 | XS2397352233 |
| DE000NLB3UX1 | XS2397372850 |
| DE000NWB0AP2 | XS2407985220 |
| FR0013511615 | XS2412060092 |
| FR0013534443 | XS2419364653 |
| FR00140033E4 | FR0012790327 |
| FR0014003RL9 | GB00BM8Z2V59 |
| FR0014004016 | XS2431784441 |
| FR0014004EJ9 | CND100009HB1 |
| FR0014006UI2 | CND100009JH4 |
| IE00BFZRQ242 | CND10000CPD7 |
| JP316572AMA6 | CND10000H6B4 |
| JP339170AM65 | CND10000H8W6 |
| JP365820AMC5 | CND10000J7Q8 |
| JP377530AKA4 | CND10000L024 |
| XS1317148580 | CND100010K22 |
| XS1550149204 | CND100017F71 |
| XS1626191107 | CND100018D15 |
| XS1711039591 | CND100018DB1 |
| XS1828046570 | CND100018DX5 |
| XS2063288190 | CND100018GF5 |
| XS2068071641 | CND10001MX11 |
| XS2069304033 | CND10001MXY4 |
| XS2100269088 | CND10001RTM6 |
| XS2194790262 | CND100026YC8 |
| XS2199484929 | CND10002LRV2 |
| XS2230307006 | CND100034297 |
| XS2234568983 | CND100039ZV8 |
| XS2240278692 | CND100039ZW6 |
| XS2243052490 | CND100039ZX4 |
| XS2268340010 | CND10003DG37 |
| XS2282707178 | CND1000458V7 |
| XS2287879733 | CND100045LG6 |
| XS2291905474 | CND100045MP5 |
| XS2314675997 | CND100046K79 |
| XS2331604079 | *XS*1279561465[1] |

[1]implausible offer yield to maturity

## APPENDIX F: SIMULATION PYTHON CODE

```
#!/usr/bin/env python3
# -*- coding: utf-8 -*-
"""
# This code was written by Arbian Halilaj for the Master's Thesis at the
# University of St. Gallen.
# Supervisor: Prof. Jana Mareckova
# For questions contact arbian.halilaj@student.unisg.ch
"""

# MONTE-CARLO SIMULATION

import random
import numpy as np
import pandas as pd
import math
import numpy.random as nrand
from econml.dml import CausalForestDML
import matplotlib.pyplot as plt

random.seed(20212022)

# Set parameters
n_sim = 1000 # Number of simulations
dim_x = 10 # Number of Confounders
n = 1000 # Number of Observations
m = 100 # Number of Issuers
z = 1 # Dependency Factor (Higher = More Dependent)

#CIR Process parameters
all_time = 1000 # Amount of time to simulate
all_delta = 1/252 # Delta, the rate of time e.g. 1/252 = daily, 1/12 = monthly
all_sigma = 0.3 # Volatility
```

```
gbm_mu = 0.2 # Annual drift factor for geometric brownian motion
cir_a = 0.5 # Rate of mean reversion
cir_mu = 2 # Long run average interest rate
all_r0 = 1 # Starting interest rate value

def brownian_motion_log_returns(all_time, all_delta, all_sigma):

    sqrt_delta_sigma = math.sqrt(all_delta) * all_sigma
    return nrand.normal(loc=0, scale=sqrt_delta_sigma, size=all_time)


def geometric_brownian_motion_log_returns(all_time, all_delta,
                                          all_sigma, gbm_mu):

    wiener_process = np.array(brownian_motion_log_returns(all_time, all_delta,
                                                          all_sigma))
    sigma_pow_mu_delta = (gbm_mu - 0.5 * math.pow(all_sigma, 2.0)) * all_delta
    return wiener_process + sigma_pow_mu_delta

def cox_ingersoll_ross_levels(all_time, all_delta, all_sigma, cir_a=0.0,
                              cir_mu=0.0, all_r0=0.0):

    brownian_motion = brownian_motion_log_returns(all_time, all_delta,
                                                  all_sigma)

    # Setup the parameters for interest rates
    a, mu, zero = cir_a, cir_mu, all_r0

    # Assumes output is in levels
    levels = [zero]
    for i in range(1, all_time):
        drift = a * (mu - levels[i-1]) * all_delta
        randomness = math.sqrt(levels[i - 1]) * brownian_motion[i - 1]
        levels.append(levels[i - 1] + drift + randomness)
    return np.array(levels)

def issuer_effect(n,m,z):

    issuer_list = list(range(1, m + 1))
    issuer = np.random.choice(issuer_list, size=n, replace=True)
```

```
    issuer = pd.DataFrame(issuer)
    df = issuer.sort_values(by=0)

    dfs=pd.DataFrame()
    for i in range(1, m+1):
        df_i = issuer.loc[issuer.iloc[:,0]==i,:]
        len_df_i = len(df_i)
        bonus = z * np.random.uniform(0, 1) / 100
        bonus_list = [bonus] * len_df_i
        dfs = dfs.append(bonus_list, ignore_index = True)

    df.reset_index(inplace=True)
    df[1] = dfs[0]
    df = df.drop('index', axis=1)

    return df

def dgp1(dim_x, n, m, z, all_time, all_delta, all_sigma, cir_a=0.0,
         cir_mu=0.0, all_r0=0.0):

    x = np.random.normal(0,1, size=(n,dim_x)) / 100
    betas = np.array(list(range(1, dim_x + 1))) / (dim_x)
    g = (x @ betas)
    d = np.random.binomial(1, 0.2, n)

    date = list(range(0,801))
    df2 = pd.DataFrame(date)
    interest_rate = cox_ingersoll_ross_levels(all_time = all_time,
                                              all_delta = all_delta,
                                              all_sigma = all_sigma,
                                              cir_a = cir_a, cir_mu = cir_mu,
                                              all_r0 = all_r0)
    interest_rates = pd.DataFrame(interest_rate/100)
    df2[1] = interest_rates[0]
    random_date = np.random.choice(date, size=n, replace=True)
    random_date = pd.DataFrame(random_date)
    df3 = pd.merge(df2, random_date, on=0)
    effect = issuer_effect(n,m,z)
    df4 = effect.sample(frac=1).reset_index(drop=True)
    df4[2] = df3[1]
```

```
    #df4[3] = df3[0]
    df4.columns = ['Issuer', 'Issuer Effect', 'Interest Rate']
    df5 = df4.set_index('Issuer')
    df_final = np.sum(df5, axis=1).tolist()
    df_final = pd.DataFrame(df_final)

    y0 = np.random.choice(df_final[0], size=n, replace=False)
    y1 = 0.1 + g + np.random.choice(df_final[0], size=n, replace=False)
    y = d * y1 + (1-d) * y0

    return (x, d, y)

def dgp2(dim_x, n, all_time, all_delta, all_sigma, cir_a=0.0,
         cir_mu=0.0, all_r0=0.0):

    x = np.random.normal(0,1, size=(n,dim_x)) / 100
    betas = np.array(list(range(1, dim_x + 1))) / (dim_x)
    g = (x @ betas)
    d = np.random.binomial(1, 0.2, n)

    interest_rate = cox_ingersoll_ross_levels(all_time = all_time,
                                              all_delta = all_delta,
                                              all_sigma = all_sigma,
                                              cir_a = cir_a, cir_mu = cir_mu,
                                              all_r0 = all_r0)
    interest_rates = pd.DataFrame(interest_rate/100)

    y0 = np.random.choice(interest_rates[0], size=n, replace=False)
    y1 = 0.1 + g + np.random.choice(interest_rates[0], size=n, replace=False)
    y = d * y1 + (1-d) * y0

    return (x, d, y)

def cf(x,y,d):

    est = CausalForestDML(discrete_treatment=True)
    est.fit(Y=y, T=d, X=x, W=None)
    effect = est.effect(x)
    ate = np.mean(effect)
    return(ate)
```

```python
def simulation(n_sim, n, dim_x, m, z, all_time, all_delta, all_sigma,
               cir_a=0.0, cir_mu=0.0, all_r0=0.0):

    all_results = np.empty( (n_sim, 1, 2) )  # initialize for results

    # Loop through many simulations
    for i in range(n_sim):
        # Run DGP1
        x, d, y = dgp1(dim_x, n, m, z, all_time, all_delta, all_sigma,
                       cir_a=0.0, cir_mu=0.0, all_r0=0.0)
        all_results[i,0,0] = cf(x,y,d)

        # Run DGP2
        x, d, y = dgp2(dim_x, n, all_time, all_delta, all_sigma,
                       cir_a=0.0, cir_mu=0.0, all_r0=0.0)
        all_results[i,0,1] = cf(x,y,d)

    return all_results

results = simulation(n_sim, n, dim_x, m, z, all_time, all_delta,
                     all_sigma, cir_a=0.0, cir_mu=0.0, all_r0=0.0)

def plot_results(results,truth):

    plt.figure()
    plt.hist(x=results[:,0,0], bins='auto',
             color='red',alpha=0.5,label="CF (no i.i.d )")
    plt.hist(x=results[:,0,1], bins='auto',
             color='blue',alpha=0.5,label="CF (i.i.d")
    plt.axvline(x=truth,label="truth")
    plt.legend(loc='upper right')
    #plt.title('DGP' + str(dgp))
    plt.show()

plot_results(results,0.1)
```

Average Treatment Effect (ATE) Average Treatment Effect on the Treated (ATT) Heterogeneous Treatment Effect (HTE) Conditional Average Treatment Effect (CATE) Swedish Krona (SEK) Green Bond Principles (GBP) Climate Bonds Initiative (CBI) Ordinary Least Squares (OLS) Causal Forest (CF) Propensity Score Matching (PSM) Coarsened Exact Matching (CEM) Conditional Independence Assumption (CIA) Augmented Inverse Probability Weighting (AIPW) Stable Unit Treatment Value Assumption (SUTVA) identically and independently distributed (i.i.d) Data Generating Process (DGP)